

A LEVEL OF CARE INDEX: DEVELOPMENT AND COMPARATIVE
EVALUATION OF A COMPUTER-AIDED UTILIZATION REVIEW SELECTOR METHOD

by

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B.A., City University of New York at Brooklyn College 1967
M.S., University of California, San Francisco 1974

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ABSTRACT

Rebecca Fuhrer, M.Sc.

The purpose of this study has been to develop and evaluate a computerized decision model to select potentially inappropriately located acute care hospitalized patients for the utilization review function of the Professional Standards Review Organization (PSRO).

A hospital's Utilization Review Committee can be accorded delegated PSRO status if it can demonstrate continued effectiveness in meeting its objectives of assuring appropriate utilization while ensuring the quality of care. By focusing on the procedure for patient selection, the effectiveness as well as efficiency of utilization review should be enhanced.

Most strategies for identifying the above referred to patients are based on the use of length of stay data, with the expectation that changes in level of care need will coincide with certain time intervals during the patient's hospital stay relative to length of stay norms.

An alternative selection procedure based on the medical services required by the patient is proposed. Statistical methodology (Multiple Logistic Discrimination Method) has been used to develop a mathematical model capable of differentiating patients requiring acute care hospital level of care from those who potentially do not. A medical services

classification system which encodes the health care environment in level of care terms has also been developed. It is used by the discriminant analysis to determine the subset of optimally discriminating variables for acute care hospital level of care assessment.

The computerized decision model is significantly better at predicting the patients who should be selected for review and the patients who need not be reviewed than the length of stay guidelines proposed by the PSRO. The costs of each selection method need to be evaluated.

The combined effort of the expertise of health care professionals in the subjectively defined medical services classification and clustering, and the power inherent in the statistical methodology used to empirically differentiate patterns, has yielded a mathematical model which approximates a complex decision process.

12

To My Parents,

S. and Z. Fuhrer

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CONTENTS

Chapter	Page
I INTRODUCTION	1
Introduction	1
PSROs and Utilization Review	2
Utilization Review Objective - A Level of Care Decision	4
A Concurrent Utilization Review System	6
Case Selection in Utilization Review	10
Presentation and Critique of Several Case Selector Methods	10
Levels of Care Criteria in Case Selection for URMDs	13
Computer-Aided Case Selection	14
Development of a Computerized Level of Care Selector Model	16
Summary	18
Notes	19a
II DISCRIMINATION METHODOLOGY	20
Introduction	20
Basic Concepts of Discriminant Analysis	21
Bayes' Theorem in Discrimination	26
Logistic Model in Discrimination	30
Logistic Discrimination in Utilization Review Selector Method	34
Summary	36
Notes	37a
III METHODOLOGY	38
Introduction	38
Experimental Design	38
Sampling Procedure	40
Patient Data for Decision Making	41
Sequential Information Acquisition for Level of Care Determination	42
Reliability of URNC Level of Care Assignment	46
Predictive Validity of the Nurse Judgments	50
An Index of Agreement for Reliability and Validity Assessment	52
Data Base	56
Length of Stay Data	56
Levels of Care Data	59
Application of Discrimination Methods for Level of Care Allocation	63

Chapter	Page
Methods for Comparative Evaluation of L.O.C.I. and L.O.S. Selector Models	65
Notes	69a
 IV DEVELOPMENT OF A CLASSIFICATION AND CODE FOR MEDICAL SERVICES	
Introduction	70
Introduction to Classification	72
Medical Services Classification Analysis	74
Classifying the Medical Services	81
Codification of Medical Services Profiles	82
Conversion from Service Classes to Service Clusters	83
Summary of Classification of Medical Services	89
Notes	93a
 V RESULTS	
Introduction	94
Description of the Sample	94
Evaluation of Inter-Reviewer Agreement on Level of Care Assignments	97
Inter-Nurse-Reviewer Reliability	97
Predictive Validity of Nurse Reviewers' Judgments	102
Inter-Physician Reviewer Reliability	102
Nurse-Physician Agreement	105
Summary of Reliability and Validity Results	107
A Discriminant Model for Level of Care Allocation	107
Comparative Evaluation of L.O.C.I. and L.O.S.	112
Evaluation of L.O.C.I. Allocations Pre and Post the 75th Percentile	113
Comparison of the Correct Allocation Rates of the Selector Models	121
Selector Sensitivity of Models	121
Selector Specificity of Models	122
Predictive Sensitivity and Specificity of Selector Models	123
Summary of Comparison of L.O.C.I. and L.O.S.	124
Outcome Analysis	125
Summary	129
Notes	129a

Chapter	Page
VI CONCLUSIONS	130
Introduction	130
Implications	132
Conclusions	136
Notes	136a
BIBLIOGRAPHY	137
APPENDICES	142
A Dictionary of a Sample of Medical Services and Associated Codes	142
B Utility Curves for Service Code Clusters As a Function of Age and PRN/Non-PRN Factors . . .	171
C Stepwise Variable Selection	196
D Seven Variable Logistic Function on Estimation Set	217
E Individual Records of Evaluation Set Including Level of Care Index	223

LIST OF FIGURES

Figure	Page
1.1 A Concurrent Utilization Review System	8
2.1 Values on Variables X_1 , X_2 For Members of Group 1 and Group 2	24
2.2 Density Function for Group 1 and Group 2 Values of $d(\underline{X})$	25
3.1A Report I Part A - Current Orders (Medical Services Profile)	43
3.1B Report I Part B - Demographic, Diagnostic Information, Outdated Orders	44
3.2 Report II - Discharge Report	45
3.3 Decision Flowsheet for Level of Care Determination . .	47
3.4 Sequential Information Acquisition for Level of Care Determination	48
3.5 Nurse Reviewer Judgments and Group Assignments	51
3.6 L.O.S. Selector Model Review Date Assignments	58
4.1 Schematic Representation of Conversion from Current Orders to Service Code Cluster Pattern	93
5.1 Histogram of Lengths of Stay for Entire Study Sample .	98

LIST OF TABLES

Table	Page
3.1 Example of a Patient's Medical Services Profile	60
3.2 Variables and Service Code Cluster Definitions	62
4.1 Different Level of Care Facilities and Examples of Services Expected to Provide	71
4.2 Classification and Codification System for Medical Services	80
4.3 Conversion of a Patient's Medical Services Profile to a Coded Medical Services Profile	84
4.4 Variables and Service Code Cluster Definitions	90
4.5 Conversion from the Service Code Profile (example) to a Service Code Cluster Pattern	91
5.1 Frequency of Observations by Unit and Estimation/ Evaluation Sets	95
5.2 Frequency of Observations by Group Assignment and Estimation/Evaluation Set	96
5.3 Inter-Nurse-Reviewer Agreement Matrix for the Entire Study Sample	100
5.4 Inter-Nurse-Reviewer Agreement Matrices for Estimation/Evaluation Sets	101
5.5 Inter-Physician-Reviewer Agreement Matrix	103
5.6 Nurse Coder-Physician - 1 Agreement Matrix	106
5.7 Optimal Discriminators for Level of Care Allocations .	109
5.8 L.O.C.I. Allocation Matrix for Estimation Set	111
5.9 Comparison of Admit and Discharge Diagnostic and Length of Stay Information	114
5.10 Pre/Post 75th Percentile Subset Contingency Tables for Current Diagnosis	116
5.11 Pre/Post 75th Percentile Subset Contingency Tables for Discharge Diagnosis	117

LIST OF TABLES (Continued)

Table	Page
5.12 L.O.C.I. and L.O.S. Allocation Matrices for Pre 75th Percentile Evaluation Subset (Current D_X)	119
5.13 L.O.C.I. and L.O.S. Allocation Matrices for Pre 75th Percentile Evaluation Subset (Discharge D_X)	120
5.14 Summary of Comparative Evaluation of L.O.C.I. and L.O.S. Selector Models	126
5.15 Outcome Analysis of L.O.C.I. and L.O.S. Allocations . .	128
6.1 Optimal Discriminating Variables for Inappropriate Utilization	133

CHAPTER I INTRODUCTION

I.0 Introduction

The objective of this dissertation is the development and evaluation of a computerized decision model to aid in the utilization review function of the Professional Standards Review Organization (PSRO) program (PL92-603). The selection of patients for review has a direct impact on the benefits and costs of the PSRO program, and has been the subject of many research endeavors.¹⁻⁵ A selector model is a procedure or algorithm which determines the sample of patients in the hospitalized population who should be reviewed. Most selector models, computer based and otherwise, use length of stay information as an indicator of which patients to review. The increased use of computer technology to support the selection procedure gives rise to the possibility of developing more effective selector models based on additional or other information. Decision modelling is the approach which is used in this research study to develop a computerized selector model.

This chapter will (1) introduce the reader to PSROs and utilization review, (2) discuss the decision process to arrive at utilization review decisions, (3) describe a concurrent utilization review system, and (4) describe a PSRO recommended selector model and propose a level of care decision model for selecting patients for utilization review.

I.1 PSROs and Utilization Review

The Professional Standards Review Organization program was enacted on October 30, 1972, as part of the 1972 Amendment to the Social Security Act. The PSRO Program Manual, published by the Department of Health, Education, and Welfare, on March 15, 1974, specified that the responsibility of PSROs would be to "review the health care provided to patients under the Medicare, Medicaid, and Maternal and Child Health programs and make judgment on the medical necessity and quality of the care rendered to those patients. In addition, PSROs are to determine whether care is proposed to be provided or has been provided at a level of care which is most economical yet consistent with the patient's medical care needs".⁶ Thus, the PSRO program is intended to accomplish two basic purposes: (1) to assure the quality of care, and (2) to assure the appropriate utilization of health care services. PSROs rely on the principles of peer review and the use of explicit criteria to improve quality of care by identifying problems and correcting them through a variety of educational programs.⁷

Since the PSRO Manual has made no precise definition of quality of care, in this study it is defined as the provision of the appropriate services, at the appropriate times, in the appropriate amounts, at the appropriate level of care. Traditionally, when measuring the quality of care, hospitals and physicians have focused almost exclusively upon medical audit. This focus, while assuring that the services delivered to a patient are appropriate for his/her diagnosis or medical problem, devotes little systematic attention to the location of these services. If a patient is inappropriately located at an acute level of care,

quality of care is adversely affected in that the delivery, amount, and timing of services received by the patient are not consistent with his/her medical care needs. Patient location is an important factor in measuring quality of care, in addition to its patent relevance to cost of care, and is of primary importance to utilization review.

The PSRO objective of assuring the appropriate utilization of health care services, is an expansion of previously legislated utilization review functions. Technically speaking, utilization review has been in existence since the enactment of the Medicare legislation in 1965, but now the PSRO "retains responsibility for assuring the continued effectiveness of that review".⁶ "Utilization Review", as defined by the Joint Commission on Accreditation of Hospitals, "is a form of peer review or medical care evaluation for the intended purpose of periodic review of the utilization of the facilities and of the diagnostic, nursing and therapeutic resources of the hospital, with respect to both the availability of their resources to all patients in accordance with their medical care needs and the recognition of medical practitioners' responsibility for the cost of health care".⁸

Prior to the PSRO legislation, reviews usually were conducted on a retrospective basis. The PSRO program, however, requires two types of reviews to be performed concurrently, that is, while the patient is in the hospital. Concurrent reviews provide the opportunity for corrective action when it is necessary, which was not the case for retrospective reviews. The concurrent reviews consist of Admission Certification Reviews which assure the need for admission to an acute care hospital and Continued Stay Reviews which assure that the patient continues to

require the services of an acute hospital.

The legislation encourages that the responsibility for these reviews be at the local level. Hence, a hospital's utilization review committee can apply for delegated status, i.e., assume the responsibility for ongoing reviews, and the PSRO will delegate said responsibility if the committee has demonstrated that it is effective in its review process. The PSRO periodically assesses the continued effectiveness of delegated utilization review committees. If the committee's performance is considered inadequate the delegated status can be rescinded, resulting in external jurisdiction for the hospital.

I.2 Utilization Review Objective - A Level of Care Decision

To satisfy the goals of utilization review, the utilization review committee must determine the most economical level of care facility which can provide the medical services a patient needs. It is to determine if a patient is appropriately located in an acute hospital.

According to Medicare guidelines, a patient is appropriately located in an acute hospital facility if the following statements about the patient are applicable:

- a. The services the patient is receiving cannot ordinarily be safely and adequately performed by the average, nonmedical, rational person without direct supervision of trained medical or paramedical personnel,

and

- b. The patient requires direct skilled nursing services (excluding observation) frequently, i.e., at least once a day,

or

the unstabilized condition of the patient requires the skills of a nurse to detect and evaluate the patient's need for possible modification of treatment or institution of medical procedures,

and

- c. The patient requires constant availability of medical services provided by a hospital and not available in skilled nursing facilities.⁹

Thus, a patient is considered appropriately located in an acute hospital if (s)he is receiving a level of care which can only be furnished in a hospital. The level of care is determined by the type, number, and/or intensity of a combination of physician, skilled nursing, and ancillary services a patient is receiving. If it is determined that a patient requires a level of care available in a skilled nursing facility or other non-hospital setting, the patient can be considered to be misutilizing the hospital setting because presumably (s)he could receive the needed care in a less costly environment.

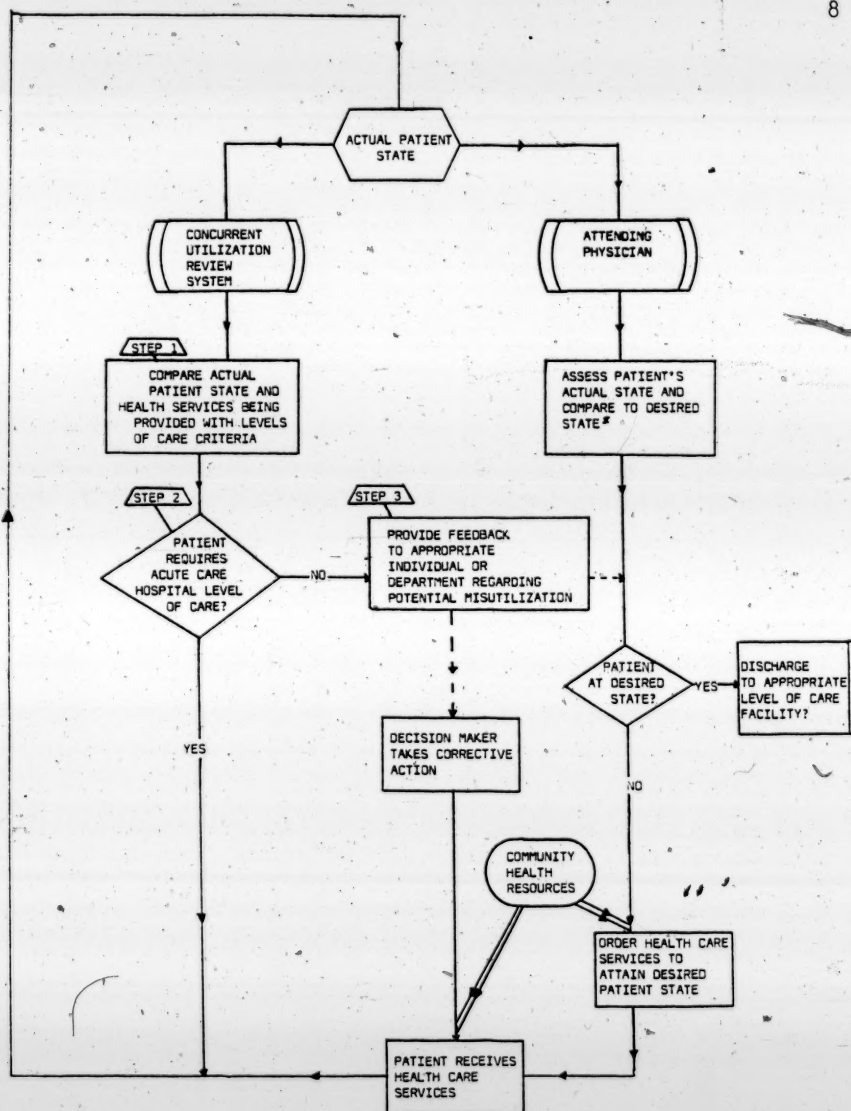
The levels of care concept grew out of work done in the field of progressive patient care. Progressive patient care is an organizational solution which classifies patients according to their needs.¹⁰ The cost of hospitalization is relative to the amount of care received. In the course of an illness a patient may require several levels of care. For example, (s)he may be admitted to the intensive care unit, when stabilized move to a conventional unit, and then be transferred to a skilled nursing facility prior to returning home. Levels of care can be viewed as a continuum from intensive care at one end of the continuum to no medical care needed at the other end. In view of medical and/or practical considerations, a patient need not necessarily require various levels of care or changes in location during the course of a hospitalization.

I.3 A Concurrent Utilization Review System

The PSRO requires that the level of care required by a patient be assessed at prespecified time intervals, i.e., on admission and during the patient's hospitalization at points determined by the diagnosis or problem or surgical treatment. The assumption is that these guidelines will ensure the effectiveness of the review process in meeting its objective of minimizing misutilization of health care services facilities. The requirements can increase substantially the time commitment on the part of utilization review committee members. A well organized concurrent utilization review system is necessary so as to ensure the efficient use of the committee members' time while not jeopardizing the institution's delegated PSRO status.

A utilization review system consists of the committee members, physician (URMD) and other health care personnel, as well as administrative support staff. A concurrent utilization review system is designed to conduct reviews during the patient's hospital stay. One type designed according to cybernetic control theory is based on the principle that a system (be it an organization, or an individual, etc.) will regulate itself if it is provided feedback that it is functioning incorrectly. To be effective it is essential that the feedback be explicit and timely.¹¹ The system seeks to identify the patients who need subacute hospital care (Figure 1.1) and provides feedback to the attending physicians in hospitals about the actual and desired use of health facility resources. Ideally the feedback is then used by the physician and/or hospital to regulate itself.

The organizational structure of the utilization review system can vary. For example, URMDs can review all the patients requiring review, make the level of care decisions, where necessary provide feedback to the attending physicians and perhaps to the hospital departments. In fact, the legislated system specifies that a URMD decide when to notify the attending physician since PSROs are based on peer review.¹² However, the use of URMDs to perform all the concurrent reviews required has several important drawbacks: (1) Physician time is a highly limited resource and is best spent providing direct patient care. It is poor use of this resource to review cases that are appropriately utilizing the hospital. (2) Concurrent reviews are not the top priority objective of URMDs given that they are all practicing physicians. Under the best conditions, a URMD allocates a limited amount of time



* "DESIRED PATIENT STATE" is affected by information on alternative health care facilities

FIGURE 1.1 A CONCURRENT UTILIZATION REVIEW SYSTEM

each day for review, but given the limitations, the timeliness of the feedback is compromised. (3) Recent findings indicate that when URMDs were forcibly involved in the decision process the feedback to attending physicians was less effective.¹³

Case selection for utilization review can be a means for resolving the problems discussed above. Criteria can be used in selecting cases for the URMD, thereby using his or her time more efficiently. Also, providing timely feedback permits corrective action, minimizes inappropriate utilization,¹³ hence, not jeopardizing the delegated status of the committee.

A nonphysician reviewer, for example a Utilization Review Nurse Coordinator, URNC, can be employed to select cases for review. This position is recognized by the PSRO program for assisting with the required paperwork and determining cases for URMD review. Various criteria exist for determining which cases the URNC should identify for the URMD. Depending on the selection procedure chosen, the URNC can be minimally involved or can be involved through step 3 of the flowchart illustrated in Figure 1.1, having direct contact with attending physician and hospital departments. The choice of information to be used, criteria for case selection and organization of the utilization review system affect the effectiveness and efficiency of the process.

I.4 Case Selection in Utilization Review

I.4.1 Presentation and Critique of Several Case Selector Methods

PSROs are requiring that length of stay by diagnosis be the criterion for determining the day for conducting the continued stay review. With few exceptions, they are requiring that continued stay reviews must be conducted by the 50th percentile length of stay by diagnosis or surgical procedure and if the patient is considered appropriate on that day, the next review be conducted on the 75th percentile length of stay, and then the 90th percentile length of stay. This assumes that for many patients the 50th (or 75th or 90th) percentile length of stay may coincide with the moment the level of care may be changing from acute hospital to another level. It also precludes the identification of misutilized days prior to the 50th percentile, between the 50th and 75th percentiles, as well as between the 75th and 90th. The efficacy of this method has not been evaluated.

Various strategies have been developed for selecting patient charts to be reviewed retrospectively by the Utilization Review Committee. The factor common to most of the selection methods was length of stay by diagnosis (e.g. see Wolfe).¹ The underlying assumption for these methods was that patients whose length of stay fell outside the acceptable range of limits for a given diagnosis had a high probability of being inappropriate utilizers of an acute hospital. By selecting cases in this manner, physician time would not be wasted reviewing patient charts who had not "misutilized" the acute hospital. However, this assumption, did not permit the assessment of possible

misutilized days for "normal" lengths of stay patients.

Additional variables such as age, sex, and type of treatment could be used to specify differences among categories of patients.

Although the categorization could make the selection process more sensitive to differences between patients, "the use of a single criterion variable such as length of stay may be insufficient to separate appropriate and inappropriate utilization with any degree of success".¹⁴

Emphasis was placed on length of stay in the reasonable belief that the great majority of hospital misutilization would be found in the latter stage of hospital stays.¹⁵ Observations by Rosenfeld et. al.,¹⁶ in their study of reasons for prolonged hospital stay led them to conclude from a review of case data that it would be unrealistic to classify the patient's institutional requirements according to length of stay or chronicity of illness. No relationship was found between length of stay and the need for acute hospital stay. Their findings have been extended to shorter hospital stays by the work of Gertman, Bucher,¹⁷ and Zimmer.¹⁸ They found that the majority of inappropriate days were found in non-longstay cases, actually 65% of the inappropriate days occurred in cases where the length of stay was below the 50th percentile of the matched PAS diagnosis group.

These results were then interpreted as showing that the data indicate that there is no positive relationship between inappropriate days and length of stay deviations from statistical norms for disease categories. This raises a serious question about the validity of using statistical length of stay measures as a basic audit or regulatory mechanism to control unnecessary hospital utilization.¹⁷

In the Gertman and Bucher study the determinant of hospital level of care was the intern's response (the intern responsible for the patient's care) to a question requesting the major reason for the patient's previous day in the hospital. Restuccia and Holloway¹⁹ used explicit criteria to arrive at a level of care decision and obtained results similar to those found by Gertman and Bucher.¹⁷

These various studies illustrate the inadequacy of this type of emphasis which can lead to the attitude that if a patient has reached the average length of stay that patient should or must be ready to leave the hospital irrespective of individual medical necessities.¹⁵

McClain recognized this shortcoming and approached the problem by looking for additional criterion variables which would be useful in case selection. By using physician-developed, explicit criteria and non-physicians applying the criteria, the cases selected for the URMDs should in the aggregate have a higher probability of having misutilized days. The objectives of this utilization case selection program would make use of both statistical screening and screening based on pre-established medical criteria applied by non-physicians.^{14,20} By modelling the utilization review decision process of physicians, he developed a decision aid in case selection for non-physicians. The model was developed for one diagnostic group (gall bladder disease), and the fact that it is diagnosis-dependent presents the problem of developing comparable models for each diagnostic group, or at best, for each class of similar diagnostic groupings.

The retrospective case selection methods described could be adapted for concurrent reviews but there are drawbacks to each. The

first relies solely on length of stay cut-offs. As already stated, it would miss misutilized days in the "normal" lengths of stay range. The second method is diagnosis-specific thereby making it very cumbersome to develop and apply the criteria.

1.4.2 Levels of Care Criteria in Case Selection for URMDs

Explicit criteria and non-physician reviewers can be effective in case selection for the URMDs.²⁰ Given that the purpose of the continued stay reviews is the identification of inappropriately located patients as a function of level of care needed, level of care criteria should be the criteria used by the URNC (the non-physician reviewer).

Levels of care criteria are diagnosis independent. The criteria are developed by the Utilization Review Committee and specify the types of services which can only be provided at a hospital level of care. To arrive at a level of care decision the URNC uses the criteria and rules for their application. The rules for applying the criteria have been extracted from the Medicare Hospital and Extended Care (Skilled Nursing) Facility Manuals,⁹ and translated into a level of care decision flow-sheet for the URNC (as illustrated by Figure 3.3). A detailed explanation of the decision process is discussed by Holloway et. al.²¹

The appropriate level of care is a function of the medical services needed by the patient as well as the resources available in the community. The community resources affect the generation of institution-specific criteria. The attending physician's current orders specify the medical services needed by the patient. For each day of hospital stay the patient can be characterized by a medical services

profile, e.g. the current orders. The medical services profile changes during the course of hospitalization. Some services can be provided only in a hospital, whereas others may be provided in various health care settings, including hospitals. The medical services profile is the primary information source used by the URNC when deciding on the appropriate level of care.

The URNC and the decision flowsheet are the selector method for the URMDs. This case selection method provides an approximation of the decision to be made by the URMD. By the use of URMD-developed criteria, physicians are in effect guiding the URNC's decisions. A URMD first becomes involved in an individual decision when the URNC requires assistance in cases not evidently complying with the criteria. The review process decisions remain in the domain of physicians (i.e. criteria specification), yet physician time is used efficiently because they only become directly involved by exception.

1.4.3 Computer-Aided Case Selection

Computer technology can be and is being used to assist the URNC. For example, the system developed at the Laboratory of Computer Science, Massachusetts General Hospital, provides administrative support necessary to maintain the patients' files, determines automatically the length of stay review date based on diagnosis and associated length of stay norms, and collects pertinent data about each patient for subsequent reviews and analysis.⁴

A more sophisticated computer supported patient classification system has been developed²² and is being used for utilization review at

Yale-New Haven Hospital.³ This utilization review system groups patients based on variables such as primary diagnosis, age, sex, type of surgery, service, and type of secondary diagnosis. The variables and their associated values that define particular groups vary for each group and were determined by their medical and statistical significance. Lengths of stay norms for each of these patient groups determine the review dates.

Systems such as these assume that patients in the same diagnostic category or patient group have equivalent medical services profiles and that the 50th, 75th, and 90th percentiles are good predictors of level of care changes in the profile.

Computerized evaluation of an individual's medical services profile should provide a better indication of a level of care change. In a hospital with a computer-based medical record system, a model which approximates the URNC's decision making, can screen each patient every day and select for URNC review only those patients whose medical services profile indicate a significant probability of inappropriate hospital utilization. Computer-based administrative support systems may be acceptable when the patient information is limited, that is, patient identification, age, diagnosis, etc. However, when more pertinent information (i.e. medical services) to level of care assessment is available, predictive capability must be increased.

I.5 Development of a Computerized Level of Care Selector Model

The concept of level of care as a function of services needed by the patient has been proposed.¹⁵ When 10 URNCs were presented with lists of current orders (patient medical services profiles), they could reliably make level of care decisions.²³ Thus, the following hypotheses are posited:

Hypothesis 1: Patients who may be inappropriately located in an acute hospital are characterized by a medical services profile (i.e. current orders) which differs from that of patients who are probably appropriately located.

Under this hypothesis, discrimination methodology will be used to develop a mathematical model capable of differentiating the medical services profiles of one patient group, SELECT FOR REVIEW --- possible inappropriate location, from the other, SELECT NOT FOR REVIEW --- probable appropriate location. In the assessment of a profile the value assumed by the model will be an index of the level of care needed by the patient. Henceforth, it will be referred to as Level of Care Index, or L.O.C.I.

Expert opinion and statistical methods will be used in the model development. Incorporating expert opinion should enhance the medical validity of the results obtained from the application of the statistical techniques. Medical experts will define a set of variables which represent the medical services which can be requested in the patient

care process. Then they will determine the utility of the presence of different levels of these variables. The statistical technique will be used to empirically determine the weight or relative importance of the optimally discriminating variables so that the sum of the weighted variables produces a discriminant equation for selecting possible sub-acute hospital level of care patients.

Hypothesis 2: Inappropriate utilization is more accurately predicted by a level of care index (L.O.C.I.) than by length of stay by diagnosis (L.O.S.)

Although Hypothesis 1 may be accepted, it may predict as well as length of stay percentile cut-off points. The two models will be evaluated to ascertain whether L.O.C.I. is a more efficacious predictor than L.O.S.

Hypothesis 3: When non-computer based information is added, probable inappropriate location is more accurately predicted by a level of care selector model than by a length of stay selector model.

The models under consideration are selecting patients for URNC review; selecting patients whose services profiles were not sufficient to make a confident decision on required level of care. If the addition of non-computer based information frequently causes a change of the level of care decision, then the efficacy of each selector model could be

affected.

When using computer-based information only, the URNC can classify patients as probably appropriately located or possibly inappropriately located and therefore seek further information (Hypothesis 1). When the URNC adds further information, the patient groups are "APPROPRIATE" --- probably appropriately located --- or "INAPPROPRIATE" --- probably inappropriately located. It is for those patients who are considered probably inappropriately located that a feedback message is initiated to the individual(s) (e.g. URMD, attending MD, discharge planning department, etc.) who can take corrective action. Hypothesis 3 seeks to evaluate each model's predictive ability for the probably appropriately located or probably inappropriately located groups --- the confident decision of the URNC.

1.6 Summary

The choice of patients reviewed has an impact on the utilization review process. The selection process should be capable of identifying as many of the inappropriately located patients without unnecessarily reviewing many appropriately located patients. Various approaches exist for predicting when a patient should be reviewed. Computer support for case selection has been primarily administrative and based on limited patient information, i.e., most often length of stay by diagnosis. A computerized model of the level of care decision process is proposed.

A comparative evaluation of the level of care and length of stay selector models will be conducted. The measures of performance are:

- 1) the selector sensitivity of each model --- the ability to identify the

inappropriately located patients (possible and probable), 2) the selector specificity of each model --- the ability to identify the appropriately located patients (possible and probable), 3) predictive sensitivity and specificity of each model --- the informational value of a model's predictions, i.e. the probability that the model's prediction is correct. Chapter II will discuss the theoretical approach, discriminant analysis, chosen for model development. Chapter III will describe the experiment designed to test the hypotheses posited. Chapter IV presents a classification system for medical services that provides the ability to define a set of variables for computerized level of care decision making. Results obtained and comparative evaluation are the subject of Chapter V, and the implications of the results are discussed in Chapter VI.

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CHAPTER II DISCRIMINATION METHODOLOGYII.0 Introduction

Deciding on the appropriate level of care for a patient can be viewed as an allocation* problem. Classification is the process of organizing into meaningful relationships the members of a heterogeneous population of objects, individuals, or diseases¹, whereas, discrimination is a process or rule which enables one to allocate an individual to the correct population when the individual's membership in a group is not known². Various empirical and subjective methods have been used in medicine to develop systems for automated diagnosis, prognosis, and to select between alternative treatments. Discriminant analysis is one empirical approach which has been shown to be useful. Lachenbruch³ provides an exhaustive survey of methods available for discrimination. A Multivariate Logistic Function (a transformation of a linear discriminant function) will be used in this research to construct a discriminant function which separates acute hospital level of

* Allocation, in its general sense, refers to a procedure which places an individual or object into separate groupings. Therefore, it encompasses classification, discrimination, assignment, categorization, etc. Due to the fact that this dissertation involves various types of allocation problems, henceforth, allocation will refer to predictions of the selector models, and assignments will refer to the decisions arrived at by the decision makers. Thus, the selector model allocates whereas the decision maker assigns. Classification will be used for the procedure which organizes the medical services into classes of medical services.

of care from non-acute hospital level of care patients. The rationale for the use of this approach will be discussed in the context of comparable endeavors in health care and taking into account the nature of the data. A brief conceptual description of discriminant analysis will be provided first, followed by a detailed explanation of the Logistic Discrimination Method and its relationship to the Bayes' Theorem approach to discrimination.

II.1 Basic Concepts of Discriminant Analysis

The goal of discriminant analysis is to allocate an observation \underline{X} , where \underline{X} is a vector of $k \times 1$ predictor variables (X_1, X_2, \dots, X_k) , to one of two or more distinct groups. The group membership of an observation is unknown and the allocation to a group is based on the value of \underline{X} . Although in some situations the distribution of \underline{X} in each group is known, in most problems the knowledge of the distribution of \underline{X} is determined by a relatively small sample from the population being studied. This distribution of \underline{X} , whether known or estimated, is used in the discrimination procedure. Different methods for estimating the distribution of \underline{X} will be described in this chapter.

The strength of any decision rule or discrimination method is its accuracy or specificity. Therefore a critical objective of discriminant analysis is to minimize the error rate (or misclassification rate) when allocating an observation to a group. Since the function used to discriminate is developed from data on group samples, the assumption that the initial data are correctly classified becomes vital

to the accurate development of the discriminant function. That is, in defining groups, there exist one or more variables that allow us to establish the groups.³ The allocation of an individual observation is based on the degree of relatedness of the variables to each group. It is desirable to find a subset of the variables which can best allocate an observation to the correct group.

The discriminant function is a means of combining the information from predictor variables in order to discriminate, as well as possible, between individual observations. A linear combination or a transformed linear combination of the variables is often used as a discriminant function. An optimum weight is determined for each variable used in the function. The method used for determining the weights depends upon the rule for optimization; e.g., minimizing the total probability of misclassification (Maximum Likelihood) or minimizing the maximum probability of misclassification in any one group (Minimax Rule).

A conceptual description of a discriminant function is as follows:

Let G_1 and G_2 be two mutually exclusive and exhaustive groups to which an observation \underline{X} can be allocated

A linear discriminant function with 2 variables is:

$$d(\underline{X}) = \beta_0 + \beta_1 X_1 + \beta_2 X_2$$

where $d(\underline{X})$ is the value of the discriminant function
for observation \underline{X}

X_1, X_2 are the predictor variables that take on
values for each observation \underline{X}

$\beta_0, \beta_1, \beta_2$ are the calculated weights

If $d(\underline{X}) = 0$ is the optimal decision boundary, then the following classification rule may be used:

if $d(\underline{X}) \geq 0$ then assign \underline{X} to G_1

if $d(\underline{X}) < 0$ then assign \underline{X} to G_2

This rule discriminates between individuals that belong to G_1 and G_2 . Figure 2.1 represents the set of all possible combinations of X_1 and X_2 . The point (X_1, X_2) for each member of Group 1 is represented by G_1 , and similarly for Group 2 by G_2 . It can be seen from Figure 2.1 that the two groups tend to occupy different regions of the space, with some overlap. The amount of overlap affects the misclassification rate.

Figure 2.2 represents the density function (distribution of the values) of $d(\underline{X})$ for Group 1 and Group 2.

The use of a discriminant function can be viewed as a test of the following hypotheses:

Hypothesis 1: Observation \underline{X} is a member of Group 1

Hypothesis 2: Observation \underline{X} is a member of Group 2

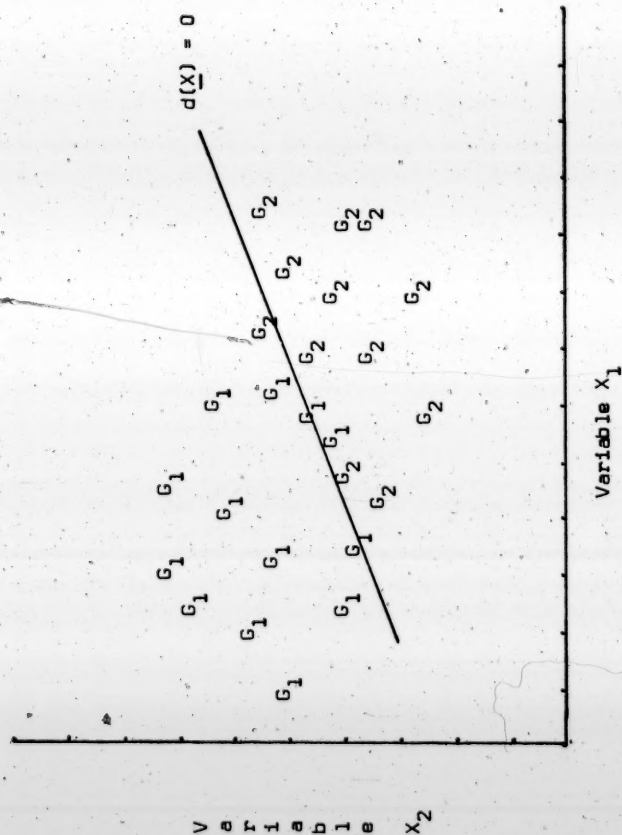


FIGURE 2.1 VALUES ON VARIABLES X_1 , X_2 FOR MEMBERS OF GROUP 1 AND GROUP 2

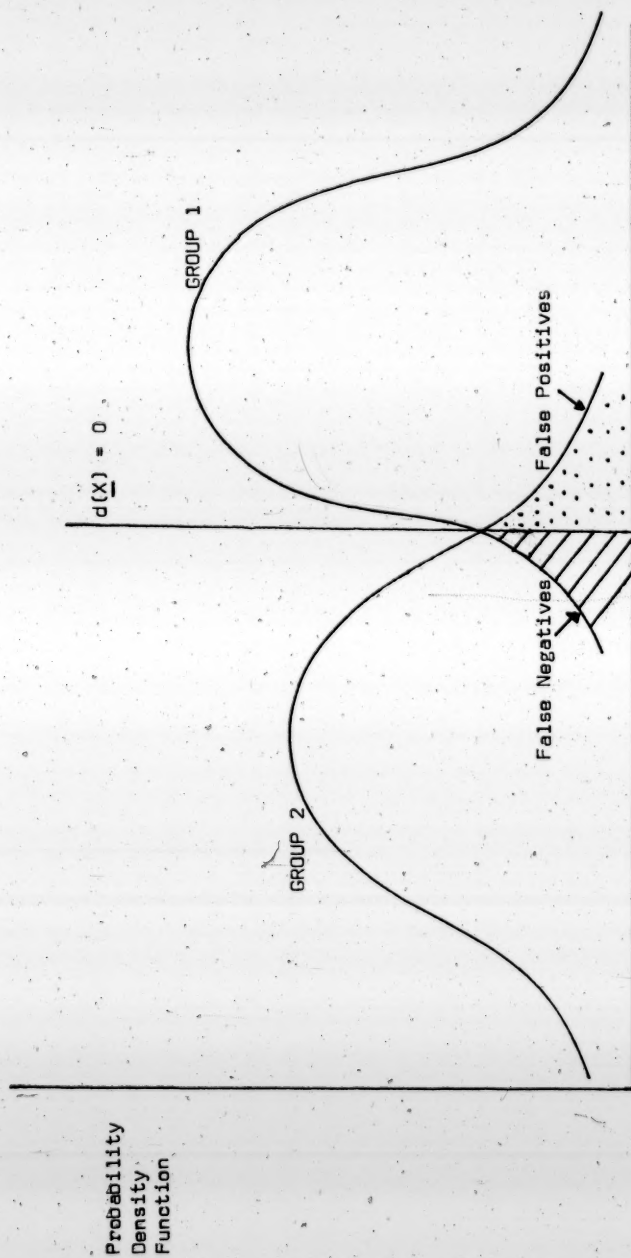


FIGURE 2.2 DENSITY FUNCTION FOR GROUP 1 and GROUP 2 VALUES OF $d(X)$

The possible outcomes of the classification procedure are:

- (i) Accept H_1 when H_1 is true (True Positive)
- (ii) Accept H_2 when H_1 is true (False Negative)
- (iii) Accept H_1 when H_2 is true (False Positive)
- (iv) Accept H_2 when H_2 is true (True Negative)

In Figure 2.2 the False Negatives are represented by the lined area and the False Positives are represented by the dotted area. The goal of the discriminant function is to minimize these two areas.

II.2 Bayes' Theorem in Discrimination

Bayes' Theorem is one approach which can be used for discrimination purposes. If an observation has a posterior probability p_1 of belonging to G_1 and a posterior probability p_2 of belonging to G_2 , then the Bayesian approach would allocate the observation to G_1 if $p_1 > p_2$, and to G_2 otherwise. This approach minimizes the expected probability of misclassification.

For the purpose of simplicity, the following discussion of Bayes' Theorem is limited to the case of two groups, G_1 and G_2 . Bayes' Theorem states that the probability that an observation X belongs to group G_1 is

given by:

$$\Pr(G_i|\underline{X}) = \frac{\Pr(G_i)\Pr(\underline{X}|G_i)}{\Pr(G_1)\Pr(\underline{X}|G_1) + \Pr(G_2)\Pr(\underline{X}|G_2)} \quad \text{for } i=1,2$$

where $\Pr(G_i)$ is the prior probability of G_i

$\Pr(\underline{X}|G_i)$ is the conditional probability or likelihood of \underline{X} given G_i

$\Pr(G_i|\underline{X})$ is the posterior probability of G_i given \underline{X}

Assuming knowledge of the prior probabilities and the likelihoods, the posterior probability is calculated for G_1 and G_2 . The following classification rule is then used to allocate observation \underline{X} to a group G_i :

Let Bayes' Odds be equal to the ratio $\frac{\Pr(G_1|\underline{X})}{\Pr(G_2|\underline{X})}$

Now, if Bayes' Odds ≥ 1 then allocate observation \underline{X} to G_1

if Bayes' Odds < 1 then allocate observation \underline{X} to G_2 .

The prior probability can be calculated from the sample or one can assume equal priors and assign a probability of 0.5 to each. A minimax solution is achieved by assuming equal priors.⁴ If the X_k (the variables which make up the vector \underline{X}) are binary and assumed

independent, then $\Pr(\underline{X}|G_i)$ can be calculated by

$$\Pr(\underline{X}|G_i) = \prod_k \Pr(X_k|G_i) \quad (\text{Independence Model})$$

Bayes' Theorem has been proposed as a theoretical basis for computer-assisted diagnosis (see for example Ledley and Lusted⁵⁻⁸). Its usefulness in classification is based on a universe of "known" mutually exclusive, exhaustive and infallibly determined groups (or diagnoses). Efforts in the field of computer-assisted decision making usually have dealt with a situation where there is a small number of possible disease groups to which an individual can be assigned. Gorry et. al.⁹ used Bayes' Theorem to sequentially update the probability that an individual presenting with the symptoms of acute oliguric renal failure had one of fourteen possible diagnoses. As more information was obtained about the patient, the probability that the patient had a given disease was calculated. Medical expert opinion was used to estimate a priori probabilities of each disease group for an individual with the presenting problem and the conditional probabilities for a symptom or sign in each of the disease groups. Ninety per cent of the time the program agreed with experienced nephrologists. Although their obtained correct classification rate was reasonably high, the authors identified problems which needed further resolution before "computer consultant" systems would be useful. One issue they raised is that of symptom non-independence.

Frequently the assumption of independence of symptoms is made when applying Bayes' Theorem in medical decision making even as it is

recognized that this assumption is inaccurate. Small data samples have made it difficult to determine joint probability distributions. The accuracy of subjective estimates of joint probability distributions would be questionable. However, confidence in Bayes' Theorem, as well as the difficulties in obtaining joint probabilities have minimized the criticisms of this assumption.

The consequences of the independence assumption were investigated by Norusis and Jacquez.¹⁰ Clinicians incorporate symptom interdependencies in their diagnostic thought processes, yet most mathematical models tend to disregard or minimally utilize the information present in correlated observations. Symptom interaction is a serious problem in statistical approaches to classification. Elashoff, et. al.¹¹ studied the relation of 2 out of n dichotomous items in a classification problem. They found that discrimination could be increased by choosing positively correlated items and decreased by choosing negatively correlated ones. This indicates that trying to use only uncorrelated variables may have a detrimental effect on the classification system.¹⁰

Theoretically, the full multinomial model (all possible outcomes) is the optimum theoretical distribution, however, the model's performance is seriously hampered by small samples. For models of moderately separable groups, Norusis and Jacquez found that including second-order interactions in the model substantially increased the accuracy of the results over the full independence approach many investigators use.

For the problem studied in this dissertation, (a) the groups are not easily separable, (b) interactions exist in the minds of URNCs and

URMDs when using the available information in making a level of care decision¹², and (c) the data used in decision making has been dichotomized.

In addition to the independence and the full multinomial models, a variety of statistical models exist which can be used to estimate multivariate binary distributions. The linear discriminant function is one approximation which incorporates second-order correlations.

Although binary data do not satisfy some of the assumptions of the linear discriminant function, the robustness of the method to deviations from both normality and equality of covariance matrices¹³ makes its use plausible in this allocation problem. The fact that it incorporates second-order correlations and withstands deviations from underlying assumptions, makes the linear discriminant function the logical method to be used. The next section will show how the linear discriminant function is used to calculate posterior probabilities and its relationship to Bayes' Theorem.

II.3 Logistic Model in Discrimination

The Multivariate Logistic Function is calculated by the use of a logarithmic transformation of the linear discriminant function. It provides a means to allocate an observation to a group, as well as an estimate of certainty with which the observation may be allocated. The estimate of certainty is the posterior probability, and is calculated without the direct calculation of the likelihood or conditional probability of X in each group.

From linear regression theory we can assume that Y is linearly related to a set of predictor variables, X_1, X_2, \dots, X_k . Thus,

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k \quad (1)$$

where Y is the dependent or predicted variable

X_1, X_2, \dots, X_k are the predictor variables

$\beta_1, \beta_2, \dots, \beta_k$ are the weights associated with each variable X_k

In discriminant analysis, Bayes' Odds is the value one is trying to calculate. In equation (1) above, the coefficients (the Betas) are estimated by the maximum likelihood method¹⁵ and a value for Y is calculated. (The linear discriminant program used for stepwise variable selection estimates the Betas by the use of the minimax rule.) Since the goal is to allocate an observation to a group, one needs to know which group Y is most likely to belong to. The logistic function transforms the non-normalized linear discriminant function into the interval, which is actually the probability of allocation into Group 1 (posterior probability).

The Logit of p , where p is the posterior probability (i.e.

$\Pr(G_1 | \underline{X})$, is defined as:

$$Y = \ln \left(\frac{p}{1 - p} \right)$$

Now using this transformation and equation (1) we obtain

$$\frac{p}{1-p} = e^Y = e^{(\beta_0 + \sum \beta_k X_k)}$$

$$\text{So, } p = \frac{e^Y}{1 + e^Y} = \frac{1}{1 + e^{-Y}}$$

which is called the multivariate logistic function.

The classification rule is:

$$\text{If Logit of } p \quad \begin{cases} \geq 0 & \text{then allocate } \underline{X} \text{ to } G_1 \\ < 0 & \text{then allocate } \underline{X} \text{ to } G_2 \end{cases}$$

The rationale for the use of the Logit is related to the lack of knowledge about the likelihood of \underline{X} as well as the desire to know the certainty with which \underline{X} has been allocated to one group or the other. The predicted values are necessarily in the range $[0,1]$ and reflect the classification certainty factor, which is the same as the posterior probability obtained from Bayes' Theorem. The following steps illustrate how the results obtained from the logistic function are similar to those obtained from Bayes' Theorem in the case of a multi-normal distribution in each group.

Let Π = prior probability of G_1

$1-\Pi$ = prior probability of G_2

$f_1(\underline{X})$ = multivariate distribution of \underline{X} in G_1 (the likelihood)

$f_2(\underline{X})$ = multivariate distribution of \underline{X} in G_2 (the likelihood)

p = posterior probability that \underline{X} belongs to G_1

(equivalent to $\Pr(G_1|\underline{X})$)

The probability that a given observation \underline{X} belongs to G_1 , is equal to ¹⁰

$$p = \frac{f_1(\underline{X})}{f_1(\underline{X}) + f_2(\underline{X})(1-\Pi)}$$

$$= \frac{1}{1 + ((1-\Pi)/\Pi)(f_2(\underline{X})/f_1(\underline{X}))}$$

If $f_1(\underline{X})$ and $f_2(\underline{X})$ are multivariate normal, then

$$\frac{(1-\Pi)f_2(\underline{X})}{f_1(\underline{X})} = e^{-(\beta_0 + \sum \beta_k X_k)}$$

$$\text{and } \Pr(G_1|\underline{X}) = p = \left(1 + e^{-\beta_0 - \sum \beta_k X_k}\right)^{-1} = \frac{1}{1 + e^{-Y}}$$

where β_1 are the coefficients of the logistic discriminant function estimated by maximum likelihood.

Although the method is optimal if the observations are multivariate normal, the posterior probability can be calculated for \underline{X} by approximating the distributions of $f_1(\underline{X})$ and $f_2(\underline{X})$ even if they are not multivariate normal. When the distributions of \underline{X} given G (i.e. $f_1(\underline{X})$)

are known or can be estimated subjectively, the Bayesian approach provides a good discrimination rule. It has just been shown how the logit transformation allows us to arrive at the same allocation rule by the use of approximations or empirically-determined estimates.

Armitage, for example, used a logit transformation to predict the prognosis of patients with advanced breast cancer. He wanted to determine the predictive variables for remission of the disease so that when a new patient would be seen, the decision for type (if any) of ablation would be a function of the pattern of discriminating variables combined with ablation in predicting prognosis. He found that ablation, mastectomy, urinary steroids, the log of time (either from time first seen or time from mastectomy to ablation), and the interactions of these variables, are good predictor variables. His results of the effect on prognosis of the choice of ablative procedure accords well with the comparison provided by the randomized trial of Atkins et. al.¹⁷ with a clear indication in favor of one type of ablation in the prognosis for the first year after ablation.^{18,19,20}

II.4 Logistic Discrimination in Utilization Review Selector Method

In the research undertaken in this dissertation, the predictor variables, the X_i , are clusters of medical services. The medical services were subjectively classified into the X_i by utilization review decision makers (procedure described in Chapter IV). In view of the preceding discussion, an empirical approach seems appropriate for deriving the weights or probabilities associated with the X_i . Actually, deriving the weights from a representative population via a methodology

such as discriminant analysis "appears to be the only proven approach where there are interaction terms in an additive model".²¹ Therefore, the empirical approach, a logistic discriminant function, has been chosen for this allocation problem.

An automated selector method which approximates expert level of care assignment will allocate a patient to $\hat{G}_S = \text{SELECT FOR REVIEW}$ or to $\hat{G}_S = \text{SELECT NOT FOR REVIEW}$ based on the service clusters present in the patient's medical services profile.

If the same population is used for both estimating the weights and computing the proportion of misclassification, the poor quality of the estimates may not be obvious. Therefore, it is desirable to use the estimated coefficients to classify a new set of individuals and then calculate the proportion of individuals misclassified. Using this procedure poor performance of the discriminant function may be obvious in a much higher misclassification rate.

The sample population was partitioned into an estimation set, used to estimate the coefficients and an evaluation set, used to evaluate the discriminant function. The proportion of observations which had been assigned to the SELECT FOR REVIEW and SELECT NOT FOR REVIEW groups, was approximately the same for the estimation and evaluation sets. The initial pattern of variables which could be used in a discriminant function most likely exceeds the number of variables which are needed for discrimination purposes. That is, there are some,

and perhaps many variables in the initial pattern with little or no discriminatory power. A procedure for selecting the variables that discriminate best is applied to the total pattern of variables. In this study, a stepwise procedure was chosen. The variable which discriminated best between the two groups was chosen first. The next variable chosen was the one which contributed most to further discrimination. This process continued until none of the remaining variables contributed substantially to discriminating between the groups. Additional details about the procedure for variable selection are included in Chapter III.

II.5 Summary

Bayes' Theorem, as well as linear discriminant analysis, are methods used in computer-aided decision processes. The problems and advantages associated with each method have been presented. A logit transformation of a linear discriminant function permits the realization of some of the advantages of each method, and therefore seemed the logical choice for the computer-aided allocation problem under consideration.

Empirical classification methodology is based on the assumption that individuals in the population from which the parameters will be estimated have been correctly classified. In situations where an absolute "true" classification is not available, expert generated criteria and rules ensure reliable classification of observations. The remainder of this dissertation describes an experiment that creates a

data base of patient days which have been reliably assigned into one of two groups, SELECT FOR REVIEW and SELECT NOT FOR REVIEW, details the information used in the assignments, and uses the data to develop a discriminant function for utilization review selection.

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CHAPTER III METHODOLOGY

III.0 Introduction

To determine the characteristics of a population which permit members of ~~that~~ population to be separated into subgroups, one must study a sample of the population and identify those characteristics which define the subgroups. An experiment was designed to accumulate pertinent data on a sample of hospitalized patients to provide the information needed to test the hypotheses under consideration. This chapter consists of the following four sections: (1) the experimental design, including tests of reliability of decision making and predictive validity of the decision process being modelled, (2) the data base construction, (3) the model development by the application of the Logistic Discrimination Method discussed in the previous chapter, and, (4) measures to evaluate the two selector models, a Level of Care Index (L.O.C.I.) and the currently mandated Length of Stay by Diagnosis (L.O.S.).

III.1 Experimental Design

An objective of this study was to develop a decision model to automatically differentiate patients who are appropriately located in an acute hospital from those who may not be. To implement the approach chosen, it was necessary to collect a data base of hospitalized patients, to record the medical services ordered for those patients, and to

obtain an expert judgment of the level of care facility a patient needed on a given day.

The study was conducted at a 464 bed, non-profit, tax-supported, short-term general community hospital serving patients under the care of their personal physicians. The hospital was chosen as the site for this project because it has a computer-based total hospital information system. The system, Technicon MIS, has been in use in the hospital since 1971. Hospital staff and physicians have had ample time to acclimate to the system; this factor is important to providing confidence in the information obtained from the system.

MIS is a real-time, computer-based system that nurses, physicians, other health care professionals and hospital administrators interact with in the delivery of health care to patients. Development of a computer-aided selector method is dependent on patient information existing in computer readable form. A major portion of the patient's medical record is stored in the computer's data base during the patient's hospitalization. Physicians enter medical orders and request results via Video Matrix Terminals installed at each nursing station, and at all other departments (e.g., clinical laboratory, radiology, etc.). In addition, a patient chart - a paper record of patient medical information - is maintained at the nursing station and subsequent to discharge filed in the medical records department. The chart, which reflects the computer medical record, is composed of periodic reports printed by MIS, and hand written entries by attending physicians and nursing staff. Various reports are printed, among which are current medical orders, laboratory results, cumulative laboratory results, x-ray reports,

medications to be administered, etc. The Utilization Review Nurse Coordinators use MIS for conducting admission and continued stay reviews.

For each patient the computer medical record documents all medical orders and examination results from the time of admission. An evaluation of the completeness and accuracy of services rendered has been conducted by an independent research institution.¹ They found that the rate of completeness and accuracy of patient information is significantly higher than prior to the installation of the system. Therefore, in this research it has been assumed that the computer medical record documents all the hospital resources the patient needs on a given day.

It is important to emphasize this assumption since the computer medical record is a major source of information used in making a level of care decision about a patient. Thus, if the completeness and accuracy of the data are inadequate or inconsistent, the predictive validity of the decision model would be compromised.

III.1.1 Sampling Procedure

Patients from the following specialty units were eligible for inclusion in the study sample: General Medical, General Surgical, Gynecology, Orthopedics, and Urology/EENT. The high intensive units (Intensive Care Unit, Transitory Care Unit, Coronary Care Unit), Psychiatry, and Pediatrics were not included in the population sampled. It was assumed that an individual in a high intensive unit required at least a hospital level of care. Psychiatric and pediatric medical

services differ from those for the rest of the hospitalized population and thus it was felt that the proposed model would not hold. Hence, patients on these units also were excluded.

The sampling period started in June 1975 and continued for a period of six months. Each day a sample of patients from each of the seven nursing units was chosen. An individual patient day is the unit of observation: thus, a patient may appear in the sample more than once. Weekend days were included. From each Unit, I , N_i patients were randomly selected for review, where N_i is proportional to the census on the unit. In addition, study sample patients who did not meet Medicare acute care hospital level of care criteria on a given day were reviewed on each subsequent day until they either a) returned to an acute care hospital level of care need, or b) were discharged. Previous studies have shown that using the same Medicare level of care criteria 10-20% of patient days are considered inappropriate.² They also demonstrated that 83% of inappropriate days are followed by at least one additional inappropriate day. For the empirical discrimination method used, a small proportion of cases in one group creates difficulties in model development. By including patient days subsequent to the "inappropriate" day the sample was biased to represent a disproportionate percentage of "inappropriate" days as well as permitting follow up on "inappropriately" located patients.

III.1.2 Patient Data for Decision Making

An abstracted form of the computer medical record was the primary information source. For each observation two computer generated reports

were printed. Report I, Part A is a list of all current orders which will be used as the predictor variables in the decision model. Report I, Part B lists demographic and diagnostic information and outdated medical orders (see Figure 3.1A and 3.1B). Report I was printed for each patient day reviewed. Report II is a discharge summary for study patients and is printed within two days subsequent to discharge (see Figure 3.2).

Report I was used for decision making (to be explained in the next section). Report II was not used for level of care decision making but was needed for the length of stay data to evaluate L.O.C.I. versus L.O.S. as selector models. In addition, it was important to know the discharge diagnosis as well as the admitting diagnosis and the diagnosis current on the day of review. The reference tables used in assigning L.O.S. review dates are based on discharge diagnostic information which is not always available, especially in the computer medical record, until the date of or sometimes after discharge. The completeness of Report II depends on the physician's use of the system to discharge the patient. Approximately 50% of the physicians enter discharge information (discharge diagnoses, and follow up information, such as where patient is discharged to) via the video matrix terminal. Other physicians include this information in the dictated discharge summary, in which case the data was abstracted from the patient's chart.

III.1.3 Sequential Information Acquisition for Level of Care Determination

The decision process for a level of care assignment consisted of

DATE OF REVIEW

PATIENT IDENTIFICATION NUMBER

MEDICATIONS:

Date Ordered: Medication, Route, Dosage, Schedule

INTRAVENOUS FLUIDS:

Date Ordered: Specific Solution, Schedule, Rate

TESTS AND SERVICES:

Date Ordered: Laboratory
Radiology
Respiratory Therapy
EKG, EEG, EMG

Schedule, Indicated if Performed but
Awaiting Results to be Entered in MIS

PATIENT STATUS:

Date Ordered: Nursing Orders
Equipment Orders
Dietary Orders
Discharge Orders

FIGURE 3.1A REPORT I PART A - CURRENT ORDERS (MEDICAL SERVICES PROFILE)

DATE OF REVIEW

PATIENT IDENTIFICATION NUMBER

AGE: SEX: MARITAL STATUS:

CITY/STATE ADDRESS:

INSURANCE(S):

ADMIT DATE:

NURSING UNIT:

ATTENDING PHYSICIAN: (written by URNC when)
(it differs from)
(admitting physician)

ADMITTING PHYSICIAN:

D: Admit or Primary
X Surgical Procedures and Date (if entered in MIS)

Data Ordered: All outdated orders in sequence by date they were discontinued.

Orders, such as laboratory requests or medications, with a specified number of doses or repetitions automatically discontinued when the limit is reached.

Other orders must be 'Discontinued' --- which is recorded as a discontinuous order, and both the date of the original order and the discontinuous order are indicated.

DATE OF DISCHARGE

DATE ENTERED:	FINAL DIAGNOSIS (PAS and ICDA Codes when available in MIS)	
DATE ENTERED:	OTHER DIAGNOSES	
DATE ENTERED:	PROCEDURED (Date Performed)	
DATE ENTERED:	Any Special Discharge Orders	
	Follow Up Visits	
	Post Discharge Medications	
	Where Discharged To	
NURSING UNIT(S)	PATIENT IDENTIFICATION NUMBER	ATTENDING PHYSICIAN
	INSURANCE(S)	

FIGURE 3.2 REPORT II - DISCHARGE REPORT

multiple stages of information gathering. Using the flowsheet (Figure 3.3) a level of care assignment was made with a new sheet used for each stage. At each stage, the URNC assigned the patient to one of the following levels of care:

- 4 = Acute Hospital
- 3 = Ideal Skilled Nursing Facility
- 2 = Existing Skilled Nursing Facility
- 1 = Home Health
- 0 = Home

The sequence was terminated when the URNC felt confident of the accuracy of her judgment. If she changed the level of care assignment she indicated which item of information produced the change. Figure 3.4 is a flow diagram for sequential information acquisition. The sequence had to be maintained in the information gathering process. Since the accuracy of a level of care index would be, in part, a reflection of the information used in its development, it was important to know the information used for decision making, and whether the information source was computer based.

In summary, for each observation the following data was collected:

- (1) Report I Part A - Current Orders
 Part B - Demographic and Diagnostic Information,
 All Outdated Orders since Admission
- (2) Report II - Discharge Report
- (3) Judgment - URNC Level of Care assignment for each
 stage of information

III.1.4 Reliability of URNC Level of Care Assignment

The decision model is to approximate the URNC's decision making process in level of care assignment. An underlying assumption is the

I. Availability of Skilled Nursing Service at All TimesMEDICARE LEVELS OF CARE CRITERIA
Medical and Surgical Patients

Definition: A skilled service is one which cannot be safely and adequately performed by the average, rational, nonmedical person without direct supervision of trained medical or paramedical personnel (including observation and instruction).

I.A. Observation. Does the unstabilized condition of the patient require "the skills of a nurse to detect and evaluate (i.e. observe) the patient's need" for possible modification of treatment or institution of medical procedures?

I.A.1. If yes, describe the unstable condition(s):

I.A.2. If yes, what about the patient is the nurse observing to keep tabs on the unstable condition?

I.A.3. If yes, when the unstable condition manifests itself, describe the skilled service (not necessarily nursing) that would be required:

I.B. Direct Service. Does the patient require direct skilled nursing services (excluding observation) every day?

I.B. Direct Service. Does the patient require direct skilled nursing services (excluding observation) every day?

I.B.1. Give the most important service(s) rendered and give frequency:

Frequency:

I.C. Patient's Condition. In view of the patient's condition, are the range (number of different skilled services) and intensity (frequency or duration) of all skilled services (e.g., extensive diagnostic tests) furnished such that they cannot be performed outside an institution?

I.C.1. If yes, what is the patient's condition such that the service cannot be performed on an outpatient basis?

I.C.2. What service(s) would be rendered if the patient's condition worsened?

I.D. Is the patient terminal?

I.D.1. If yes, describe the unstable condition:

Is the patient's condition unstable?

NO → Not Acute Hospital (Assign 1 or 0)

YES → Acute Hospital (Assign 4)

Go to II.A.

FIGURE 3.3 DECISION FLOWSHEET FOR LEVEL OF CARE DETERMINATION

II. Acute Hospital Medical ServicesMEDICARE LEVELS OF CARE CRITERIA
Medical and Surgical Patients

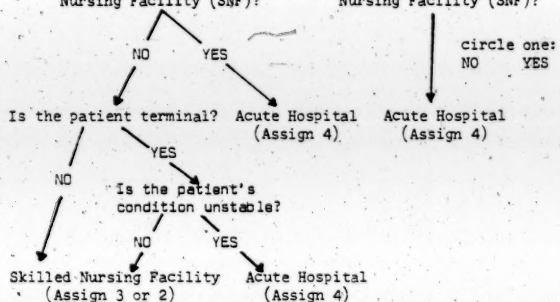
II.A. Having established that the patient requires availability of skilled nursing services at all times (or requires broad and intense skilled services in an institution), does the patient today require the constant availability of a physician?

II.A.1. If yes, why is this constant availability of a physician required?

NO
II.B. Does the patient today require the constant availability of medical services provided by an acute hospital and not provided by a Skilled Nursing Facility (SNF)?

YES
II.B. Does the patient today require the constant availability of medical services provided by an acute hospital and not provided by a Skilled Nursing Facility (SNF)?

II.B.1. Give the most important service(s) rendered (if Rehab Services are the only services, then go to the REHAB WORKSHEET II):



II.B.2. If yes, describe the unstable condition(s):

FIGURE 3.3 (continued) DECISION FLOWSHEET FOR LEVEL OF CARE DETERMINATION

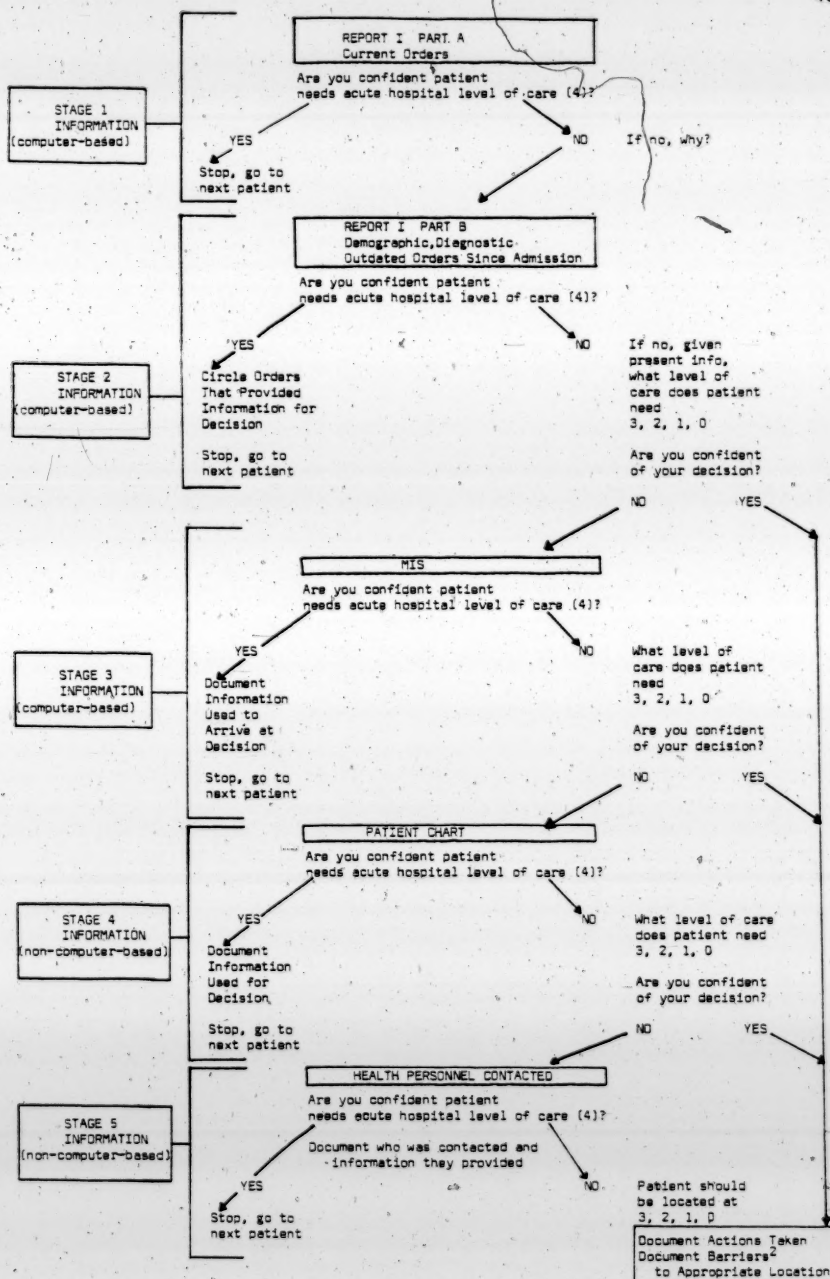


FIGURE 3.4 SEQUENTIAL INFORMATION ACQUISITION FOR LEVEL OF CARE DETERMINATION

accuracy of the URNC's judgment in making the assignment. This assumption must be verified prior to the model development. The presence of random errors in making assignments undermines the degree of lawfulness that an empirical model can uncover. Therefore, the reliability and validity of the judgments must be assessed.

The URNC can be said to be reliable in level of care assignment if she is consistent in her decision making. Thus, consistency or repeatability of results is a measure of reliability. Mutual consistency between different individuals (i.e., a consensus of opinion) is referred to as inter-reviewer reliability and is one method for determining reliability. Reliability is a necessary condition for assessing predictive validity and must therefore be established. The assessment of predictive validity of the URNC's judgments will be discussed in the following section.

The decision flowsheet abstracted from the Medicare Manual (Figure 3.3) specifies both the criteria and rules for the application of the criteria and was used to ensure intra and inter-nurse-reviewer reliability. To measure inter-nurse-reviewer reliability, another nurse, henceforth referred to as Nurse Coder, was specially trained in levels of care criteria and their application. She had previous experience in making levels of care decisions³ but did not work at the hospital. For each observation she used Stage 1,2,3 information, that is, all the information that may be available in the computer medical record, to make an assignment to the SELECT FOR REVIEW or SELECT NOT FOR REVIEW group. The computerized patient selector model is to determine which patients should be selected for review by the URNC. Thus, it is

sufficient that this is the decision to be approximated. To be capable of comparing the judgments of the URNC and the Nurse Coder, the observations the URNC had assigned to non-acute hospital level of care (any judgment less than 4) from the use of Stage 1,2,3 information were reassigned to the SELECT FOR REVIEW group, G_S . Those observations assigned to acute hospital level of care using Stage 1,2,3 information were reassigned to the SELECT NOT FOR REVIEW group, $G_{\bar{S}}$. (See Figure 3.5). An inter-nurse-reviewer reliability index as measured by a coefficient of agreement was calculated.

III.1.5 Predictive Validity of the Nurse Judgments

Validity refers to the extent that the instrument being developed is useful--that is, if it does what it is intended to do.⁴ A decision model is valid if it satisfactorily approximates the decision process. The type of validity at issue in this problem is predictive validity. Predictive validity is of concern when the purpose is to use the instrument to estimate an important form of behavior. The behavior is the criterion by which the validity of the instrument is measured.⁴

As already stated, the URNC is a screen or selector method for the URMD. An underlying assumption of Utilization Review is that ultimately only a physician is qualified to review another physician, because their experience and training provide them with a comparable body of knowledge to make decisions. A URNC has a "limited" aspect of the knowledge base and may therefore be capable of predicting or estimating what a URMD would decide with the use of a more "complete" knowledge base of medicine. The URMD's decision is the criterion by

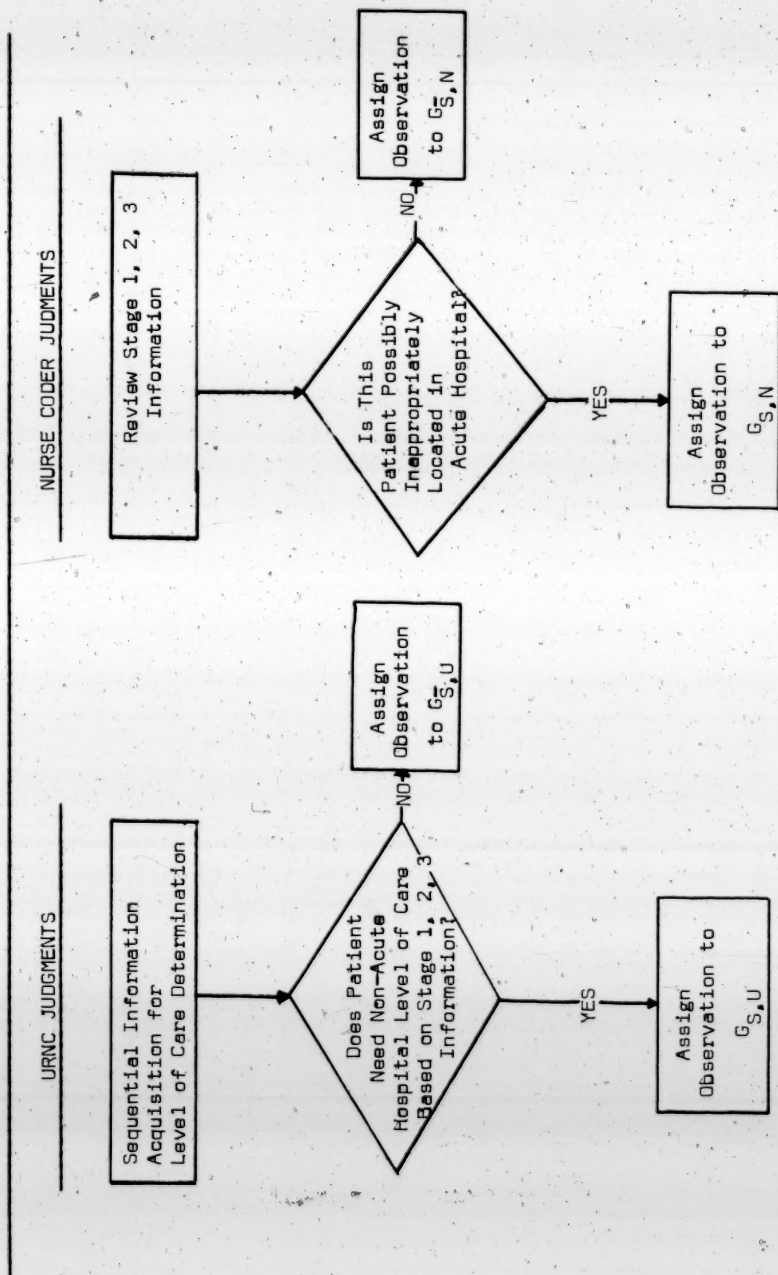


FIGURE 3.5 NURSE REVIEWER JUDGMENTS and GROUP ASSIGNMENTS

which the URNC's judgments are evaluated. Both have equal information for the specific patient but differing general knowledge about the patient's problems. How well does the URNC differentiate the patients the URMD decides need acute hospital level of care from those the URMD decides need more detailed review?

A randomly selected sample of 99 observations was used to evaluate the predictive validity of the nurse judgments. Two physicians, with extensive training and experience in utilization review and levels of care decision making, made a level of care judgment for each observation in this sample by using only computer-based (Stage 1,2,3) information. Inter-physician-reviewer reliability was calculated as well as the degree of predictive validity of the nurse judgments. The predictive validity of a model (in this case the URNC is a model for the URMD) consists of calculating the coefficient of agreement between the nurse and physician reviewers. The higher the value of the coefficient of agreement, the greater the predictive validity of the nurse's decision making.

III.1.6 An Index of Agreement for Reliability and Validity Assessment

An often used measure of reliability is the proportion of perfect agreement between the reviewers. The Chi-square test and the contingency coefficient, C ,⁵ are two other popular measures. Simple proportion of agreement does not take into account the degree of agreement which could be expected by chance alone. Chi-square and the contingency coefficient, C , measure association and not agreement per se.⁶ A valid measure of agreement should incorporate a correction for the degree of chance

agreement, it should measure agreement and not just association, and should be amenable to a test of statistical significance of the degree of agreement.⁷

Kappa, a coefficient of inter-reviewer agreement for nominal scales, provides these factors-that is (1) it measures agreement corrected for that which is expected purely by chance, (2) it is scaled from -1 to +1, where negative values indicate worse than chance agreement, 0 indicates exactly chance and positive values indicate better than chance, and (3) it has a well defined standard error which permits statistical assessment of the significance of the observed degree of agreement.⁶

The following table is presented to illustrate the components used to calculate Kappa and the approximation of the standard error of Kappa.

		DECISION MAKER A		
		j = 1	j = 2	$P_{1.} = \sum P_{o,1j}$
DECISION MAKER B	i = 1	$P_{o,11}$ $P_{e,11}$	$P_{o,12}$ $P_{e,12}$	$P_{1.}$
	i = 2	$P_{o,21}$ $P_{e,21}$	$P_{o,22}$ $P_{e,22}$	$P_{2.}$
	$P_{.j} = \sum P_{o,ij}$	$P_{.1}$	$P_{.2}$	1.0

Where $P_{o,ij}$ is the observed proportion in cell ij

$P_{e,ij} = P_{i.}P_{.j}$ and is the expected proportion in cell ij

Kappa is simply the proportion of agreement after chance agreement is removed and it is calculated by the following formula:

$$K = \frac{P_o - P_e}{1 - P_e}$$

where $P_o = \sum P_{o,ij}$ for $i=j$ and is the observed proportion of agreement
 $P_e = \sum P_{e,ij}$ for $i=j$ and is the expected proportion of agreement

An approximation to the standard error of K is as follows and has been defined as the conditional standard error by Bishop et. al.⁹ (the standard error of K , σ_K , is the square root of the $\widehat{\text{Var}}(K)$).

$$\widehat{\text{Var}}(K) = \frac{1}{N(1-p_e)^4} \left\{ \sum_{i=1}^n p_{i1} \times \left[(1-p_e) - (p_{.1} + p_{1.})(1-p_0) \right]^2 + (1-p_0)^2 \sum_{i=1}^n \sum_{j=1}^n p_{ij} (p_{.1} + p_{j.})^2 - (p_0 p_e - 2p_e + p_0)^2 \right\}$$

If N (the sample size) is large ($N \geq 100$), which is the case in this study, the sampling distribution of K will approximate normality so that confidence limits can be set in the usual way:

$$95\% \text{ Confidence Limits} = K \pm 1.96 \sigma_K$$

$$99\% \text{ Confidence Limits} = K \pm 2.58 \sigma_K$$

By evaluating the normal curve deviate, z , one can test the significance of the difference between two independent K 's:

$$z_{K1K2} = \frac{K_1 - K_2}{\sqrt{\text{Var}(K_1) + \text{Var}(K_2)}}$$

To test an obtained K for significance, that is, testing whether there is any agreement between the decision makers, or equivalently, testing the null hypothesis that K comes from a population of units for which the population $K_p = 0$, z_{K_0} is calculated as follows:

$$z_{K_0} = \frac{K}{\sigma_{K_0}}$$

The approximation to the standard error for the case of no agreement is as follows:⁸

$$\sigma_{K_0} = \sqrt{\frac{1}{N(1 - p_g)^2} (p_g + p_g^2 - \sum_i p_{i.} p_{.i} (p_{i.} + p_{.i}))}$$

Thus, Kappa permits the assessment of reliability and validity based on the degree of agreement.

III.2 Data Base

The total amount of information necessary to make decisions exceeded the quantity of data needed to test the hypotheses under consideration. Therefore, the data base created to develop and evaluate the L.O.C.I. and L.O.S. models consisted of diagnosis specific length of stay data, level of care judgment(s), and a coded version of the medical services profile (Report I Part A).

III.2.1 Length of Stay Data

The L.O.S. selector model is an adaptation of the utilization review admission and continued stay directives of the San Francisco Peer Review Organization. They in turn, have incorporated the American Medical Association and PSRO recommendations for conducting utilization review.

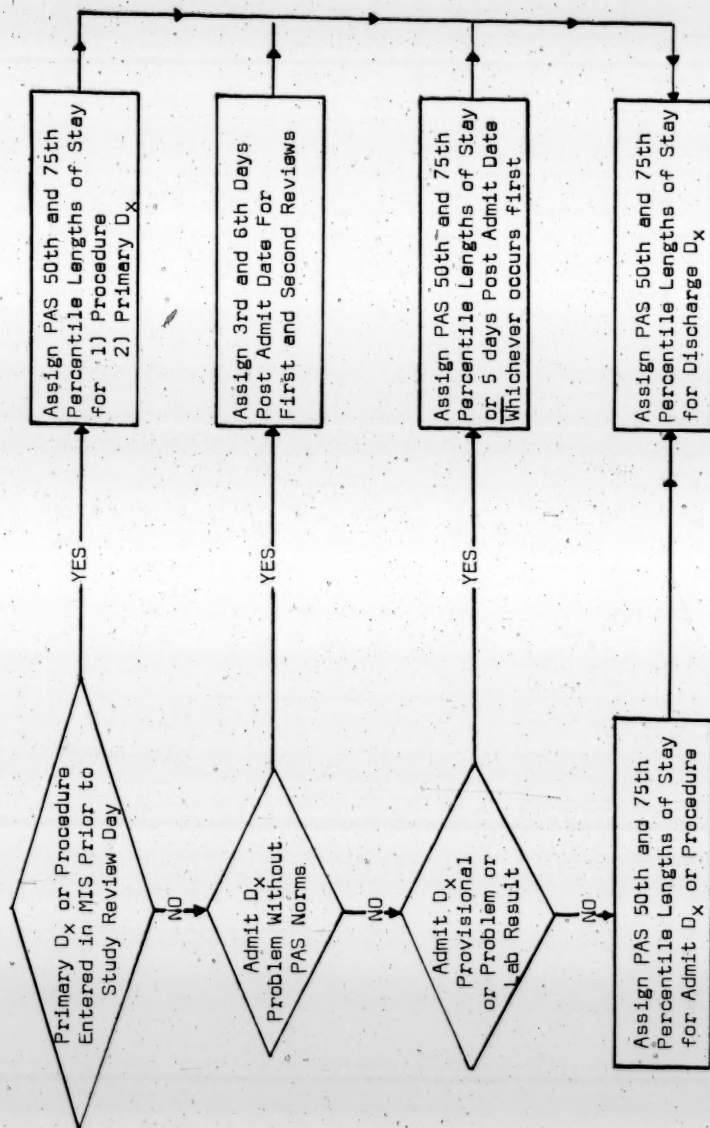
An initial length of stay assignment for the current* diagnosis determines the date of the first continued stay review. Percentile length of stay guidelines are diagnosis and age specific as defined by the Professional Activity Study (P.A.S.) for Western Region Hospitals.¹⁰

Patients are to be reviewed when their length of stay is equal to the 50th percentile length of stay for their respective diagnosis group. If determined appropriate on that day, the 75th percentile length of stay is the day of the subsequent review, and then the 90th percentile length of stay.¹¹

The following rules are used in ascertaining the "correct" length of stay assignments for the L.O.S. model: (Figure 3.6)

- 1) The 50th percentile length of stay is assigned for the admitting diagnosis. If the reason for admission is a "problem" or symptom or a provisional diagnosis, the 50th percentile length of stay or 5 days post admission, whichever occurs first, is the review date assigned. For problems or diagnoses without established criteria sets and P.A.S. norms, the first continued stay review is 72 hours after admission and every 72 hours thereafter until an established diagnosis is indicated.

* Current diagnosis refers to the diagnostic category which takes precedence in L.O.S. assignments on a given study review day. Therefore, if a primary diagnosis is entered past the date of review, the admit diagnosis is the current diagnosis.



* All PAS Assignments are Age and Surgery Adjusted

FIGURE 3.6 L.O.S. SELECTOR MODEL REVIEW DATE ASSIGNMENTS

- 2) If a primary diagnosis is entered in the computer system during the patient's stay, the associated length of stay norm takes precedence over the admit diagnosis.
- 3) If a non-minor surgical procedure has been performed and is entered, the associated length of stay norm takes precedence over the admit and primary diagnoses.
- 4) Discharge diagnoses and procedures and associated lengths of stay are documented for comparative analysis of predictability of admit versus discharge diagnoses.

III.2.2 Levels of Care Data

A Medical Services Profile is the list of current medical orders requested for diagnosing and restoring a patient to a desired state of health. In this study, a current medical order refers to any service the health care facility is providing, should be prepared to provide if a pre-specified condition arises, or has provided on the day being observed. Report I Part A is a free text representation of this information (for an example see Table 3.1).

The Technicon MIS Corporation provided a listing of all the medical orders which can be selected when using MIS. The potential volume of different medical orders far exceeds the 12,000 items on the list. This is due to the fact that most orders can be modified by attaching a schedule for performing the services, medication orders specify the medication and the route of administration, and new orders can be generated by combining existing choices. It seems almost superfluous to state that one cannot and need not be capable of uniquely

TABLE 3.1 Example of a Patient's Medical Services Profile

DATE OF REVIEW: 9/30/75
 PATIENT I.O.

MEDICATIONS:
 9/27 Cefazolin Sod.-1000 MG. IV, Q6H, (09/28 01AM - ...)
 9/27 Meperidine-10 MG to 20 MG, Slow IV, PRN Pain
 9/29 Meperidine-50 MG to 75 MG, IM, Q3H, PRN Pain
 9/29 Aspirin Supp 600 MG, # 1, PR, Q4H, PRN If Temp Over 101

IV-S:
 9/29 IV's Slow ... D5/0.45 NACL, 1000 ML, Infuse at 80 ML/HR, Then Keep Open At Present Rate: Add to IV Bottle-Potassium Chloride-Inj, 30 MEQ. in IV, Each Bottle

TESTS AND SERVICES:
 9/27 PCV Only --- Daily Starting Tomorrow
 9/28 (In Process) X-Ray: Rt Elbow, Tomorrow, (09/29)
 9/28 (In Process) X-Ray: Rt Wrist, Tomorrow, (09/29)
 9/28 (In Process) X-Ray: Rt Foot-Toes, Tomorrow, (09/29)
 9/28 (In Process) PCV Only, Daily Until Discontinued, Starting Tomorrow (09/30)

PATIENT STATUS:
 9/27 Activity, Bedrest
 9/27 Activity, Cough-Deep Breathe, Q2H When Well Reacted
 9/28 Beds,Equip: Air Mattress
 9/29 Activity, Turn Pt, Q2H
 9/29 Vital Signs, BP-P-R, Q4H
 9/28 Blow Bottles Q1H --- While Awake
 9/27 Diet: NPO-Exc-Ice
 9/28 Irrigate/Inst NG Tube, PRN With Sterile H₂O
 9/28 Irrigate Sump With Norm Saline, 20 ML, PRN
 9/28 Sump --- Connect to High Intermittent Suction
 9/29 Record I & O, Q4H

identifying each possible medical order, at least not for this decision process. It is desirable, and in this study, necessary, to be able to identify medical services in a way which provides information for a computerized approximation of level of care decision making.

A free text representation of each medical service provides too many variables for model development, computer recognition of free text is a difficult problem, and the relative importance of a service for decision making is not explicit in the free text. Many services are similar enough in the information they provide for level of care assignment that they can be identified by the same name. The reasons for using a classification scheme are numerous. I searched for, and did not find, an existing classification system for medical services which could meet the described need.

Thus, a critical objective of this research was the development of a classification system for medical services which organizes similar services into one class identified by the same code. Due to the complexity of the process, a detailed description of the evolution of a classification system and code for medical services is provided separately in Chapter IV.

To permit the reader to follow the discussion of the model development, Table 4.4 is duplicated as Table 3.2. It lists the pattern of predictor variables used to develop a discriminant function. These 30 binary variables represent the clusters of medical services that are considered useful in describing a patient day in order to determine the required level of care.

For each observation the medical services profile was first

TABLE 3.2 Variables and Service Code Cluster Definitions

Variable	Definition	Utility
X ₁	Nursing (Intensity 1, Intensity 3)	High
X ₂	Nursing (Intensity 1, Intensity 3)	Moderate
X ₃	Nursing (Intensity 5)	High
X ₄	Nursing (Intensity 5)	Moderate
X ₅	Nursing (Intensity 7)	High
X ₆	Nursing (Intensity 7)	Moderate
X ₇	Medications (Intensity 1, IV Intensity 3)	High
X ₈	Medications (Intensity 1, IV Intensity 3)	Moderate
X ₉	Medications (Intensity 3 IM & PO, Intensity 5)	High
X ₁₀	Medications (Intensity 3 IM & PO, Intensity 5) ^{Non-PRN}	Moderate
X ₁₁	Medications (Intensity 3 IM & PO, Intensity 5) ^{PRN}	High
X ₁₂	Medications (Intensity 3 IM & PO, Intensity 5) ^{PRN}	Moderate
X ₁₃	Medications (Intensity 7)	High
X ₁₄	Medications (Intensity 7)	Moderate
X ₁₅	Ancillary Diagnostic (Intensities 1, 3, 5)	High
X ₁₆	Ancillary Diagnostic (Intensities 1, 3, 5)	Moderate
X ₁₇	Ancillary Diagnostic (Intensity 7)	High
X ₁₈	Ancillary Diagnostic (Intensity 7)	Moderate
X ₁₉	Ancillary Diagnostic (Intensity 9)	High
X ₂₀	Ancillary Diagnostic (Intensity 9)	Moderate
X ₂₁	Ancillary Therapeutic (Intensity 1)	High
X ₂₂	Ancillary Therapeutic (Intensity 1)	Moderate
X ₂₃	Ancillary Therapeutic (Intensity 3, Intensity 5)	High
X ₂₄	Ancillary Therapeutic (Intensity 3, Intensity 5)	Moderate
X ₂₅	Ancillary Therapeutic (Intensity 7, Intensity 9)	High
X ₂₆	Ancillary Therapeutic (Intensity 7, Intensity 9)	Moderate
X ₂₇	Hospital Based Service	
X ₂₈	Discharge Planning Service	
X ₂₉	Physician Rendered Service (Intensities 1, 3)	Constant
X ₃₀	Physician Rendered Service (Intensities 5, 7, 9)	Constant

translated into a coded medical services profile, which was then converted to the service code cluster pattern--the pattern of predictor variables.

III.3 Application of Discrimination Methods for Level of Care Allocation

If the discrimination analysis and classification evaluation are performed on the same population, the results are biased. It is not appropriate to assume that a discriminant model that classifies at an acceptable level of accuracy on one sample will be equally successful on another sample. To avoid this criticism, and test the robustness of the discriminant model, the study population was separated into two sets. Every third observation was chosen for the set on which the model would be evaluated. The estimation set consisted of 715 observations and was used to select the best predictor variables and estimate the coefficients of the model. The evaluation set consisted of 357 observations and was used to evaluate the predictive capability of the model.

As will be discussed in Chapter IV, a list of variables was determined by expert opinion which are useful in making a decision about the level of care required by a patient on a specific day. It is to be expected that expert opinion will include variables that do not have statistical significance for discrimination and thus produce many false positives in the variable selection.

A stepwise linear discriminant procedure¹² was used to obtain a hierarchical selection of the smallest subset of variables from the initial pattern. This method rules out the medical services which are

non-contributing to the differentiation of the groups. The variables that are retained are combined to give a linear discriminant function used in the decision rule to allocate observations into the two a priori determined groups.

The stepwise linear discriminant procedure was applied to the estimation set. The dependent variable is the nurse's judgment on level of care assignment. There are 29 predictor variables eligible for inclusion, variable X_{28} , the discharge planning service variable, was recorded but was excluded from model development. The URNC, Nurse Coder and physicians were asked to disregard this order in decision making whenever it occurred. However, it was included in the service code cluster pattern because it can be used as a predictor for review independent of either model and should therefore be identifiable for separate evaluation.

The variable which discriminates best between the two groups (the one with the highest F-value) is the first one chosen to enter the discriminant equation. Subsequent variables are chosen in a stepwise manner, including at each step the best discriminating variables, while accounting for those already chosen. A variable that has been chosen for inclusion in the discriminant function can be eliminated if its associated F-value (recalculated each time a new variable enters the function) drops below a threshold value. This can occur due to an interaction between new variables chosen and variables already in the discriminant equation. The interaction affects the F-value of previously chosen variables. This process for inclusion (and rejection) is repeated until the F-value for any of the remaining variables is not

statistically significant for inclusion in the discriminant equation.

The advisability of transforming the linear discriminant function into the probability of allocating individuals into each group has been discussed. The Logistic Discrimination Method is a means of obtaining this probability. The variables selected by the linear discriminant function were used to fit the Logistic Discriminant Function. The Logit, defined as a multiple regression on the predictor variables, is computed as the logarithm of the expected proportion of the outcomes. The Logistic Discriminant Function was fit by the method of maximum likelihood. The program used¹³ calculates the estimated coefficients of the function, determines the misclassification rate, and displays a plot of the distribution of the expected Logits for the observations in each group of the estimation set.

Then the Logistic Discriminant Model was tested on the evaluation set in order to compute a Logit and allocate each observation to one of the two groups. The observation is allocated with an associated probability of membership in the group. The model's allocations will be referred to as \hat{G}_S = Model SELECTS FOR REVIEW and $\hat{G}_{\bar{S}}$ = Model SELECTS NOT FOR REVIEW.

III.4 Methods for Comparative Evaluation of L.O.C.I. and L.O.S. Selector Models

Several criteria were evaluated in order to assess, and thereby compare, the effectiveness of the L.O.C.I. and L.O.S. selector models. The following criteria were used:

a) Correct Allocation Rate

At this point in time a statistical test of the significance of an obtained allocation rate does not exist for the situation under consideration. Kappa cannot be used to measure the agreement between the discriminant model and the nurse's judgments because the decisions are not independent. The predictor variables and their associated weights representing the relative importance of a variable were determined from decisions made by the nurse. Thus, the independence assumption does not hold. The correct allocation rates will be compared as indicators of the predictive validity of the models.

Any selector model's allocations can be represented by the following table:

"TRUE" ASSIGNMENTS

<u>PREDICTED ALLOCATION</u>		G_S	$G_{\bar{S}}$
	\hat{G}_S	TP	FP
	$\hat{G}_{\bar{S}}$	FN	TN

Where: TP = True Positive
 FP = False Positive
 TN = True Negative
 FN = False Negative

The columns represent the true states as determined by expert judgment; the rows represent the model's decision.

A "positive" response by the expert or the model is the allocation of an observation to the SELECT FOR REVIEW group (G_S or \hat{G}_S). A "negative" response by the expert or the model is the allocation of an observation to the SELECT NOT FOR REVIEW group ($G_{\bar{S}}$ or $\hat{G}_{\bar{S}}$).

The Correct Allocation Rate is the proportion of True Positives plus True Negatives.

$$\text{Correct Allocation Rate} = \frac{TP + TN}{TP + FP + TN + FN}$$

b) Measures of Sensitivity and Specificity

The Correct Allocation Rate is not a sufficient measure by which to evaluate a selector model because it does not provide knowledge about the types of incorrect allocations.

Sensitivity and Specificity are measures that do provide this information about the performance of the selector models.

- b.1) Selector Sensitivity: the selector sensitivity of a model is a measure of how well the procedure under consideration selects for review those observations which experts determined should be selected for review. Therefore, the selector sensitivity of a model is a function of the proportion of True Positives.

$$\text{Selector Sensitivity} = \frac{TP}{TP + FN} = \Pr(\hat{G}_S | G_S)$$

The higher the proportion of True Positives, the greater the degree of selector sensitivity of a selector model.

- b.2) Selector Specificity: the selector specificity of a model is a measure of how well the procedure under consideration minimizes the number of observations selected for review that experts determined should not be selected for review. Therefore, the selector specificity of a model is a function of the proportion of True Negatives.

$$\text{Selector Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} = \Pr(\hat{G}_S | G_S^-)$$

The higher the proportion of True Negatives, the greater the degree of selector specificity of a selector model.

- b.3) Predictive Sensitivity and Specificity: the predictive sensitivity and specificity are two other measures of a model's performance and are related to the selector sensitivity and selector specificity. The predictive sensitivity is a measure of the predictive value of a positive response by the selector model. It is a function of the proportion of True Positives and False Negatives. Thus,

$$\text{Predictive Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} = \Pr(G_S | \hat{G}_S)$$

The predictive specificity is a measure of the predictive value of a negative response by the selector model. It is a function of the proportion of True Negatives and False Negatives. Thus,

$$\text{Predictive Specificity} = \frac{\text{TN}}{\text{TN} + \text{FN}} = \Pr(G_S^- | \hat{G}_S^-)$$

c) Outcome Analysis of Effectiveness of Selector Model

An outcome of a judgment without complete information may be a change in assignment when additional information is introduced in the decision making process. Therefore, "outcome" is defined as the confident or final decision made by the URNC.

L.O.C.I. has been developed to predict a decision based on Stage 1,2,3 information. If the URNC's decision changes often with additional (i.e., Stage 4,5) information, the true sensitivity and specificity rates of the selector models are affected. Thus, correct allocation rate, sensitivity and specificity of each selector model will be assessed also for the "confident or final" level of care assignment--the outcome.

NOTES

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CHAPTER IV

DEVELOPMENT OF A CLASSIFICATION AND CODE FOR MEDICAL SERVICESIV.0 Introduction

The medical services ordered for a patient are the data used by the URNC to decide on the level of care facility which can meet the patient's needs. The level of care an institution can provide is a function of the services it offers in the delivery of patient care. Table 4.1 lists several different level of care facilities and illustrates the services each type of facility is expected to provide. The types of services available vary between and within each institution. Some hospitals have available for use services which are not available at other institutions, e.g. one institution may have a cobalt treatment facility whereas another may not. Within an institution, however, there is great variation in the types of services available, e.g. clinical laboratory compared to intravenous medications compared to operating room facilities.

The quantity of different medical services which health care facilities offer far exceeds the number of variables which the logistic discrimination method can handle. Thus, it was imperative to reduce the potential number of variables, but in a way that could still permit the description of the level of care a patient requires and the level of care an institution provides.

There are services which share similar characteristics in the information they provide for making a level of care decision. Hence, it

TABLE 4.1 Different Level of Care Facilities and Examples of Services Expected to Provide

HEALTH CARE FACILITY	SERVICES EXPECTED TO PROVIDE
Acute Care Hospital	<p>Diagnostic and Treatment Services (e.g. Radiology, Clinical Laboratory) Within the Institution;</p> <p>Operating Room Services;</p> <p>Continuous Skilled Nursing Services - Staffing at Approximately 5 Hours Per Patient Day;</p> <p>Daily Physician Attendance;</p> <p>Rehabilitative Therapies;</p>
Ideal Skilled Nursing Facility	<p>Skilled Nursing Services (e.g. IVs, Tube Feedings, IM Medications, Catheters) Continuous Nursing Care - Post Acute - Staffing at Approximately 4 Hours Per Patient Day;</p> <p>Available* X-Ray Facilities, Clinical Laboratory, Rehabilitative Therapies;</p>
Existing Skilled Nursing Facility	<p>Nursing Services - Lower Skill Levels - Staffing at Approximately 2 Hours Per Patient Day;</p> <p>Available* Ancillary Services</p>
Home Health Agency	<p>For Patients Who Need: Intermittent Skilled Nursing Care or Physical or Other Rehabilitative Therapies; Under A Physician's Continuing Care</p>

* Available - Pre-Arrangements For Obtaining These Services in the Community

was decided to reduce the quantity of variables by organizing the medical services into classes sharing similar characteristics and identifying the classes by a meaningful code. Most of the classification efforts in the health care field have been in relation to diseases or diagnoses or surgical procedures. A classification system encoding the health care facility environment in terms of services it offers could not be found.

IV.1 Introduction to Classification

Classification is recognized as the basis of all scientific generalization and is therefore an essential element in statistical methodology.¹ Classification is also essential to decision making and is actually equivalent at a certain juncture in the decision making process. It permits the amalgamation of information, which reduces the quantity of data to be processed, a factor which is important as the quantity of data most people can use simultaneously is limited.² Therefore, classification is a reduction process, a means of forming sets for decisions.³ The classification of information process is iterative until an action decision is taken.

When "classes" of the same type of information are frequently used by various individuals, as is the case in health care, the process needs to be formalized. A classification system formalizes the process to aid in communication. A diagnosis is a name for a set of symptoms and signs; it classifies the set. When utilized by two physicians, the diagnostic label represents the set which is present in the minds of the physicians. By referencing the set with a single label or name,

multiple facts determining the label plus facts associated with the aggregate are transferred by one data item.

When developing a classification system, the classification axes are determined by the objectives of the users and the information they will need to have about a given class. Therefore, it follows, that the particular axes selected will reflect the interest of the investigator.¹ For example, the International Classification of Diseases¹ was adopted by the World Health Organization as the standard disease classification system and it evolved from an initial endeavor by the International Statistical Congress in 1853. Two individuals, William Farr, an English medical statistician, and Dr. Marc D'Espine, of Geneva, were asked to develop a uniform nomenclature and statistical classification for diseases and causes of death. They each had the same goal in mind, yet generated classes based on very different principles. Farr's classification was arranged under five groups: Epidemic diseases, Constitutional (general) diseases, Local diseases arranged according to anatomical site, Development diseases, and diseases that are the direct result of violence. D'Espine classified diseases according to their nature (gouty, herpetic, haematic, etc.).¹ The classes they formed were representative of how each perceived the classification system to be used, plus the experience and expertise of each one produced a different formulation of classes.

The classes are identified by a nomenclature. A nomenclature is a list or catalogue of approved terms for describing and recording.¹ A code is a system of rules that enables messages in the source language, i.e., the initial set of information to be transformed into a

target language or code language⁴ or nomenclature.

Let it be sufficient to state that there are usually four reasons to establish a code, and, as already discussed, they were of significant importance to the study. They are:

- a) to translate from a difficult to use source language to a language that is easier to use for a particular purpose or purposes,
- b) to decrease amount of space to record information,
- c) to supplement amount of information available in the source language,
- d) to distinguish between alternative ideas or words that are not easily distinguished in the source language.⁵

Therefore, not only will a classification system be developed, but so will a codification system to identify the classes. The code will provide the ability to use the information inherent in the class of services to make decisions and assessments about patients and facilities.

IV.2 Medical Services Classification Analysis

There are two major approaches to classification analysis: discrimination and clustering.

Discrimination techniques begin with either a priori conceptual distinctions or data divided into a priori groups and proceed to develop rules by which to separate data into those a priori categories, whereas clustering techniques use a priori selection of a measure of similarity, a criterion, and a class description to find an inherent empirical structure in data--to find clusters. Thus, discrimination is the development and application of analytical rules, the parameters of which are often derived from the data, that allow a researcher to assign or sort objects into specific categories. Discrimination uses externally supplied labels associated with each member of a set of objects to aid in establishing rules for sorting things into groups. In clustering, which may be either of objects, or of variables, we seek to find so-called data-derived groups

based on internal similarity between the objects; the definition of similarity is left to the user, as are procedures by which sorting into similar groups is accomplished.⁶

Both discrimination and clustering techniques were used in the development of the medical services classification system.

Axes for classifying the services were chosen a priori on the relative importance attributed to that category of information. The criteria for determining level of care⁷ give rise to questions which are answered by responses which fall into a combination of the following categories*:

Intensity of Service

Department Responsible for Service Performance

Individual Responsible for Service Performance

Type of Service

Two axes, or categories, the Department and Individual Responsible for Service Performance were classified according to the discrimination approach. Intensity Level and Type of Service were classified according to the clustering approach.

*category - refers to the various axes of which this classification system will comprise

class - refers to the combined four digit code ($C_1 C_2 C_3 C_4$) which will define a service

modality - refers to the values a category can assume

Category 1: Intensity of Service

Intensity of service is a function of a combination of characteristics of a medical service. A service can be so "intense" that it can be provided only on an inpatient basis in an acute care hospital. If a service is not acute care hospital based, then it can range in intensity from extremely intense to non-intense. The factors which affect intensity are:

- frequency of service in a 24 hour period;
- complexity/skill level required to perform the service;
- risk associated with performance of the service;
- route of administration (for medications and diet).

Medication intensity level is based on an interaction of the specific drug, the route of administration and the frequency of a given dosage level. As a result, medications are considered a nursing service whose intensity is a function of route of administration and very frequent administrations and/or a high risk medication. Each medication was scaled on a risk factor. If the medication itself had a higher risk than the route, the medication took precedence in intensity assignment.

The following codes identify the intensity category modalities:

- (0) Hospital based service
- (1) Extremely intense service
- (3) Very intense service
- (5) Moderately intense service
- (7) Minimally intense service
- (9) Non-intense or trivial intensity service

Category 2: Department Responsible for Service Performance

This category should be evident from the title. The Clinical Pathology does all the laboratory and pathology work. The Radiology Department does all the x-ray diagnostic and therapeutic work. Other departments, similarly, perform designated sets of medical services. Department responsible for service performance is already encoded in MIS. When an order is written by a physician, the system notifies the appropriate department(s) that the service has been requested.

The following codes identify the modalities for this category:

- (1) Clinical Pathology
- (2) Radiology (includes Radiation Therapy and Nuclear Medicine)
- (3) Nursing
- (4) Rehabilitative Therapies (includes Physical and Occupational therapy)
- (5) Respiratory Medicine (includes Pulmonary Medicine and Respiratory Therapy)
- (6) Surgery or any private physician rendered service
- (7) Electrocardiogram, Electroencephelogram or Electromyelogram Departments
- (8) Discharge Planning
- (9) Other

Category 3: Individual Responsible for Service Performance

This category specifies the individual within the Department who assumes the responsibility for the requested service.

For example, in the Nursing Department there are some services that must be rendered by an R.N., whereas other services can be under the R.N.'s supervision. For Clinical Pathology, one assumes that a technologist actually performs the test and reports the results unless a physician is required to. This category is clearly defined by the rules of each department and/or the laws of the state.

The following codes identify the modalities for this category:

- (0) M.D.
- (1) Registered Nurse (R.N.)
- (2) Under R.N. Supervision (includes L.V.N.'s, Nurse's Aides, Orderlies, Central Supply)
- (4) Therapists, Technologists, Technician - specially trained (and usually licensed) individual within an ancillary department
- (5) Dietician
- (9) no special skills required - can be members of the patient's family or the patient

Category 4: Type of Service

The type of service is the dominant purpose of the order.

The following codes identify the modalities of this category:

- (0) routine service, routine measurement, support service
- (1) observation/interpretation including monitoring
- (2) diagnostic
- (3) therapeutic
- (4) psychological/psychiatric
- (5) Traction and patient status orders
- (6) precaution and isolation
- (7) medication (includes infusions and transfusions)
- (8) procedure - surgical and non-surgical
- (9) other

Table 4.2 summarizes the definitions of the classification system. The combination $C_1C_2C_3C_4$ is the four digit service code which labels each medical order.

It is important to note that the "intensity of service" digit is based on an ordinal scale whereas the digits used in categories C_2, C_3, C_4 , are based on a nominal scale. The services with an intensity digit of 0 or 1 have a higher intensity associated with them than those with an intensity of 9. There is no indication how much more intense one level of intensity is than another or even an absolute value of the intensity for a given level. It should be recognized that ordinal scaled values cannot be manipulated mathematically but do convey information on the relative relationships between objects. Nominal scales are used to label or identify only. There is no relationship between the relative position of the digit used and the attributes of the objects being labeled, thus nominal scales also cannot be manipulated mathematically.

TABLE 4.2 Classification and Codification System for Medical Services

A four digit code which classifies services provided by health care facilities and health care practitioners. Each digit provides information about services which are in a class defined by $C_1C_2C_3C_4$.

CATEGORY 1 (C_1): INTENSITY LEVEL

- 0 = Hospital Based Service
- 1 = Extremely Intense Service
- 3 = Very Intense Service
- 5 = Moderately Intense Service
- 7 = Minimally Intense Service
- 9 = Non-Intense or Trivially Intense Service

CATEGORY 2 (C_2): DEPARTMENT RESPONSIBLE FOR SERVICE PERFORMANCE

- 1 = Clinical Pathology
- 2 = Radiology
- 3 = Nursing
- 4 = Rehabilitative Therapies
- 5 = Respiratory Therapy
- 6 = Surgery or any Private Physician Rendered Service
- 7 = Electrocardiogram, Electroencephalogram, Electromyogram
- 8 = Discharge Planning
- 9 = Other

CATEGORY 3 (C_3): INDIVIDUAL RESPONSIBLE FOR SERVICE PERFORMANCE

- 0 = M.D.
- 1 = Registered Nurse (R.N.)
- 2 = Under R.N. Supervision
- 3 =
- 4 = Therapist, Technologist, Technician
- 5 = Dietitian
- 9 = No Special Skills Required, e.g. Patient, Family

CATEGORY 4 (C_4): TYPE OF SERVICE

- 0 = Routine Service, Routine Measurement, Support Services
- 1 = Observation, Interpretation, Includes Monitoring
- 2 = Diagnostic
- 3 = Therapeutic
- 4 = Psychological/ Psychiatric
- 5 = Traction, Patient Status Orders
- 6 = Precaution and Isolation
- 7 = Medications, Infusions, Transfusions
- 8 = Procedures - surgical and non-surgical
- 9 = Other

IV.3 Classifying the Medical Services

Once the critical modalities were defined, every hospital service that can be ordered by a physician was classified according to each of the four categories. Since it is the physician who requests the services to be provided to a patient, it follows that the source vocabulary be all possible physician orders. The listing of all physician orders currently used was supplied by the Technicon MIS Corporation.

Health care professionals (two physicians and two nurses) trained in levels-of-care concepts classified each of the 12,000 medical services into each of the above categories. Each person worked independently. After all the services were classified, the group met to compare classifications. Services with total classification agreement were not discussed unless an individual raised feelings of doubt. For those services with classification disagreement or doubt, open discussion almost always led to consensus.

An expert in each "department responsible for service performance" classified the medical services in his/her domain of responsibility. There was a high level of agreement between the departmental expert and the above referred to health care professionals. Any disagreement was in the intensity of service category. When the modalities assigned to were close, the departmental expert's category took precedence. There were few occurrences of a service being classified into modalities that are distant from each other.

The health care professionals were then presented with a list of 4 digit codes and the services that had been classified into those

classes. They were asked to confirm that the services in a class belonged together, that is, that they provided the same kind of information for level of care assessment. About 10% of the services were reclassified. This procedure was repeated until there was full consensus. The departmental experts then reviewed these final lists of classified services and found less than 1% reclassification. Appendix A is a dictionary of a sample of the medical services and associated codes. It is in departmental order.

The system was designed to permit expansion when the codes within a category are no longer capable of adequately defining a service. This means that if a new medical service is developed and does not clearly fit into an existing category with its associated code, a new one will be added. In a field like medicine, where the knowledge explosion has been very rapid, and is still expanding quickly, the system needs to be easily expandable to meet new information requirements. If it is not, it would very quickly lose its utility and significance.

IV.4 Codification of Medical Services Profiles

A nurse (Nurse Coder) was trained to apply the codes to the medical services profile. The current medical services for each observation were translated into the associated 4 digit code thereby generating a coded medical services profile.

On careful examination of the medical services profile (Report I Part A) an interesting fact was observed. The date each order is written is included on the report. The URNC uses many of the orders

with a decrease in importance as the age of the order increases. Some orders are never discontinued although the probability may be close to zero that the patient is receiving the service. This is especially noticeable for PRN or conditional orders. The age and PRN/non-PRN affected the relative utility of an order to the decision making process, and therefore were also documented in the coded medical services profile. Table 4.3 illustrates the conversion from a medical services profile to a coded medical services profile.

Once all the observations were coded, we found that 80 different service codes were actually used. This quantity quickly multiplies when the age of the order and PRN/non-PRN factors are combined with the service code. In addition, an individual could have multiple occurrences of the same service code with the same and/or different age and PRN factors. The number of possible variables was still too great to perform the analyses discussed in Chapter II. Could the service codes be combined in a meaningful fashion, reducing the number of variables but retaining the information needed for a level of care selector model?

IV.5 Conversion from Service Classes to Service Clusters

To determine if the service classes could be combined and still provide the information necessary to make a level of care decision, the author and one of the physicians involved in the code development studied the list of 80 service codes actually used and the proportion of use in both the SELECT and SELECT NOT FOR REVIEW groups. Seven service clusters emerged as dominant factors which were labeled:

TABLE 4.3 Conversion of a Patient's Medical Services Profile to a Coded Medical Services Profile

DATE	MEDICAL SERVICE	CODE
DATE OF REVIEW: 9/30/75		
9/27	Cefazolin Sod.-1000 MG, IV, Q8H, (09/28 01AM - ..)	C 1317
9/27	Meperidine-10 MG to 20 MG, Slow IV, PRN Pain	3 1317
9/29	Meperidine-50 MG to 75 MG, IM, Q3H, PRN Pain	1 3327
9/29	Aspirin Supp 600 MG, 1 1, PR, Q4H, PRN If Temp Over 101	1 7327
9/29	IV's Slow ... D5/D.45 NACL, 1000ML, Infuse at 80 ML/HR, Then Keep Open At Present Rate: Add to IV Bottle Potassium Chloride-Inj, 30 MEQ, in IV, Each Bottle	A 3317
9/27	PCV Only --- Daily Starting Tomorrow	
9/28	(In Process) X-Ray: Rt Elbow, Tomorrow, (09/28)	S 9242
9/28	(In Process) X-Ray: Rt Wrist, Tomorrow, (09/28)	S 9242
9/28	(In Process) X-Ray: Rt Foot-Toes, Tomorrow, (09/28)	S 9242
9/29	(In Process) PCV Only, Daily Until Discontinued, Starting Tomorrow (09/30)	W 9142
9/27	Activity, Bedrest	
9/27	Activity, Cough-Deep Breathe, Q2H When Well Reacted	C 5323
9/28	Beds, Equip: Air Mattress	B 9320
9/29	Activity, Turn Pt, Q2H	
9/29	Vital Signs, BP-P-R, Q4H	A 3321
9/28	Blow Bottles Q1H --- While Awake	B 5323
9/27	Diet: NPO-Exc-Ice	B 5323
9/28	Irrigate/Inst NG Tube, PRN With Sterile H ₂ O	
9/28	Irrigate Sump With Norm Saline, 20 ML, PRN	
9/28	Sump --- Connect to High Intermittent Suction	
9/29	Record I & O, Q4H	A 5321

Where First Digit of CODE Represents Age and PRN/non-PRN

Numbers: PRN	Letters: non-PRN	A-R	Age in number of days
0 Day of Review	T Stat	Z	Order written day of review
1-9 Age in Number of days	W Daily	X	Order completed that day
	S Awaiting Result	Y	Order for day after review

Nursing (medications excluded)

Medications

Ancillary Diagnostic

Ancillary Therapeutic

Hospital Based Service

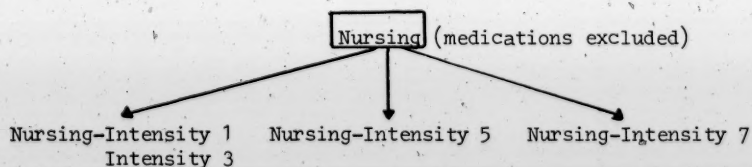
Physician Rendered Service

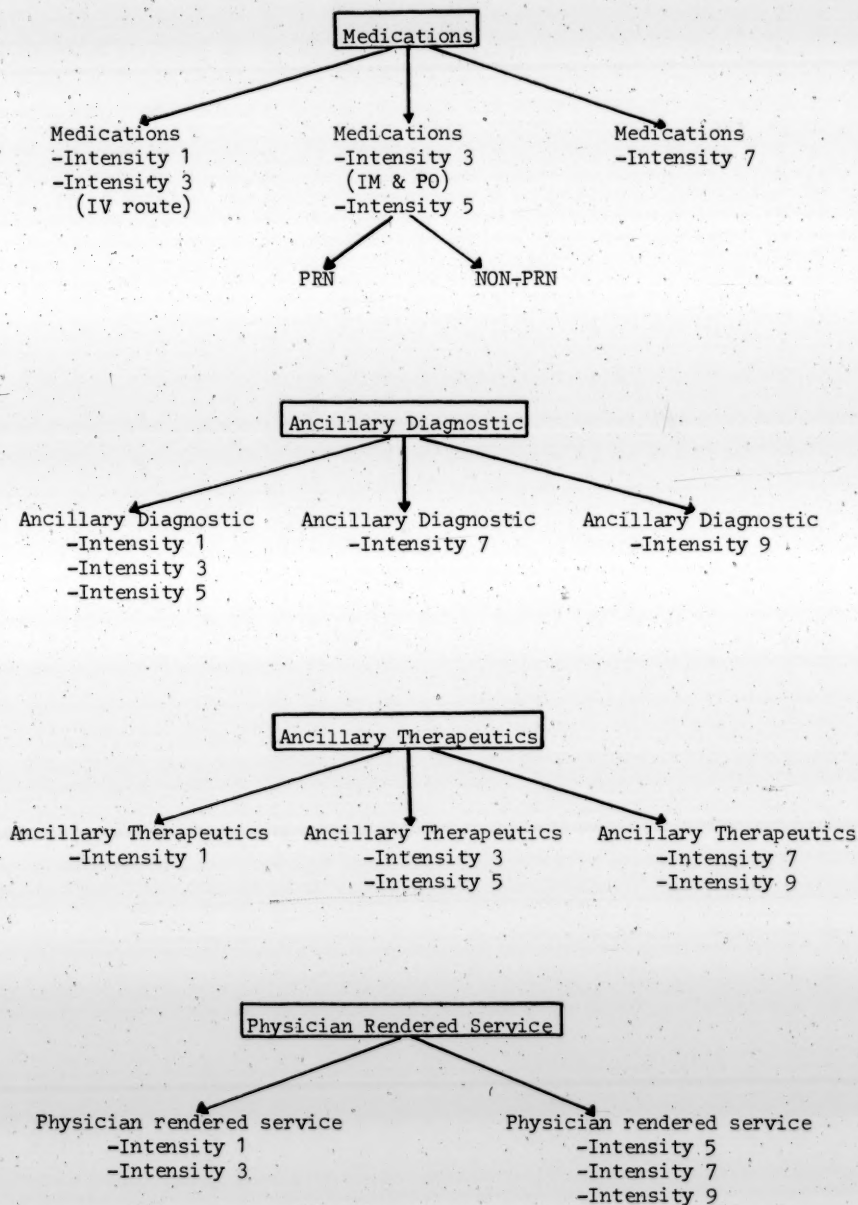
Discharge Planning

These service clusters reflect the types of criteria which are used in making levels-of-care assessment, as illustrated in the level of care decision flowsheet (Figure 3.3). This indicates that the service codes are useful in describing patient needs in terms of level of care.

The service clusters were then presented to the Nurse Coder for subjective evaluation of the usefulness or utility they had in her decision-making. She was told that she could split the clusters if important information was lost in the combination or that she could combine category modalities further.

The following service clusters were split due to the intensity factor:





(Nursing Intensity 9 and Medications Intensity 9 were eliminated because they had little or no utility in decision making.)

The 80 service codes were now reduced to seventeen useful dichotomous variables, the 15 above + Hospital Based Service + Discharge Planning Service. It had already been determined that the age and PRN/non-PRN factor affected the utility of a service code to the level of care decision. The quantity of service codes in a service cluster also affected the utility. Physician rendered services have constant utility.

For each new variable, its relative utility for the level of care decision, was obtained as a function of age and PRN/non-PRN. A separate utility curve was obtained as a function of the quantity of service codes that contributed to the presence of that variable. For the age-factor utility curves, age equal to zero was assigned a utility of 100. A zero or near zero utility level was assigned to some point further out in time. A curve connecting the two points was drawn after some intermediate points were directly obtained. The slope of the curve and the zero point were dependent on the specific service cluster and the PRN/non-PRN factor.

The same procedure was repeated for the quantity factor, only this time, assigning to quantity zero the zero utility point and a utility of 100 to a quantity greater than zero but dependent on the specific service cluster and the PRN/non-PRN factor.

Figures 1a-13a in Appendix B represent the utility curves for a service cluster as a function of age, PRN/non-PRN. It is the utility of service cluster s for age a , U_{sa} . Figures 1q-13q in Appendix B represent the utility curves for a service cluster as a function of quantity. It is the utility of service cluster s for quantity q , U_{sq} .

The final objective was to determine a utility level for a

service cluster as a function of both age and PRN/non-PRN AND quantity, $U_{s,a,q}$. Could one assess the utility of a multi-attributed consequence by assessing the utility of each attribute and then forming a weighted average? A critical aspect is the independence of the attributes. In this problem, the attributes are not independent.

Neither $U_{s,a,q} = U_{sa} + U_{sq}$ nor $U_{saq} = U_{sa} \times U_{sq}$ accurately represented or even approximated the plane defined by the combined utility of both attributes for each service cluster.

Since many of the utility curves resembled step functions, it was decided that there would not be a significant loss of information if each curve was separated into 3 regions of utility: high, moderate, low. For each curve the utility scores ≥ 80 were coded as high, a utility score > 39 and < 80 was coded as moderate and a utility score < 40 was coded as low. Rules were determined for combining the regions on the two attributes. The fact that age-PRN/non-PRN has greater utility than quantity is reflected in the rules. The following matrix represents the possible combinations:

		QUANTITY FACTOR UTILITY		
		Q-HIGH	Q-MODERATE	Q-LOW
<div style="border: 1px solid black; padding: 2px; display: inline-block;"> A G E PRN non-PRN </div>	F			
	A	A-HIGH	High	High
	C			Moderate
	T	A-MODERATE	Moderate	Moderate
	O			
	R	A-LOW	Moderate	Low

Each service cluster was represented by two dichotomous variables,

$X_{SH} = 1$ & $X_{SM} = 0$ indicates High utility of service cluster S

$X_{SH} = 0$ & $X_{SM} = 1$ indicates Moderate utility of service cluster S

$X_{SH} = 0$ & $X_{SM} = 0$ indicates Low to No utility of service cluster S

where subscript SH refers to high utility for service cluster S
subscript SM refers to moderate utility for service cluster S

The rules were applied to the service code profile of each observation and converted it to a service code cluster pattern of thirty dichotomous X_s variables which are listed in Table 4.4. The conversion of a medical services profile to a service code profile has been illustrated. Table 4.5 illustrates the same service code profile converted to a service code cluster pattern.

IV.6 Summary of Classification of Medical Services

A rationale and approach for the development of a classification system for medical services was presented. Discrimination and clustering techniques were utilized to derive rules to aid in the classification process. Medical service codes identify classes of medical services.

The service codes are qualitative representations of a patient's current orders. Because the number of possible variables was still too great for model development, a rule was developed for combining service codes (while adjusting for age of order and PRN/non-PRN factors) into service code clusters which could still be used to describe an

TABLE 4.4 Variables and Service Code Cluster Definitions

Variable	Definition	Utility
X ₁	Nursing (Intensity 1, Intensity 3)	High
X ₂	Nursing (Intensity 1, Intensity 3)	Moderate
X ₃	Nursing (Intensity 5)	High
X ₄	Nursing (Intensity 5)	Moderate
X ₅	Nursing (Intensity 7)	High
X ₆	Nursing (Intensity 7)	Moderate
X ₇	Medications (Intensity 1, IV Intensity 3)	High
X ₈	Medications (Intensity 1, IV Intensity 3)	Moderate
X ₉	Medications (Intensity 3 IM & PO, Intensity 5)	High
X ₁₀	Medications (Intensity 3 IM & PO, Intensity 5) (Non-PRN)	Moderate
X ₁₁	Medications (Intensity 3 IM & PO, Intensity 5) (PRN)	High
X ₁₂	Medications (Intensity 3 IM & PO, Intensity 5) (PRN)	Moderate
X ₁₃	Medications (Intensity 7)	High
X ₁₄	Medications (Intensity 7)	Moderate
X ₁₅	Ancillary Diagnostic (Intensities 1, 3, 5)	High
X ₁₆	Ancillary Diagnostic (Intensities 1, 3, 5)	Moderate
X ₁₇	Ancillary Diagnostic (Intensity 7)	High
X ₁₈	Ancillary Diagnostic (Intensity 7)	Moderate
X ₁₉	Ancillary Diagnostic (Intensity 9)	High
X ₂₀	Ancillary Diagnostic (Intensity 9)	Moderate
X ₂₁	Ancillary Therapeutic (Intensity 1)	High
X ₂₂	Ancillary Therapeutic (Intensity 1)	Moderate
X ₂₃	Ancillary Therapeutic (Intensity 3, Intensity 5)	High
X ₂₄	Ancillary Therapeutic (Intensity 3, Intensity 5)	Moderate
X ₂₅	Ancillary Therapeutic (Intensity 7, Intensity 9)	High
X ₂₆	Ancillary Therapeutic (Intensity 7, Intensity 9)	Moderate
X ₂₇	Hospital Based Service	
X ₂₈	Discharge Planning Service	
X ₂₉	Physician Rendered Service (Intensities 1, 3)	Constant
X ₃₀	Physician Rendered Service (Intensities 5, 7, 9)	Constant

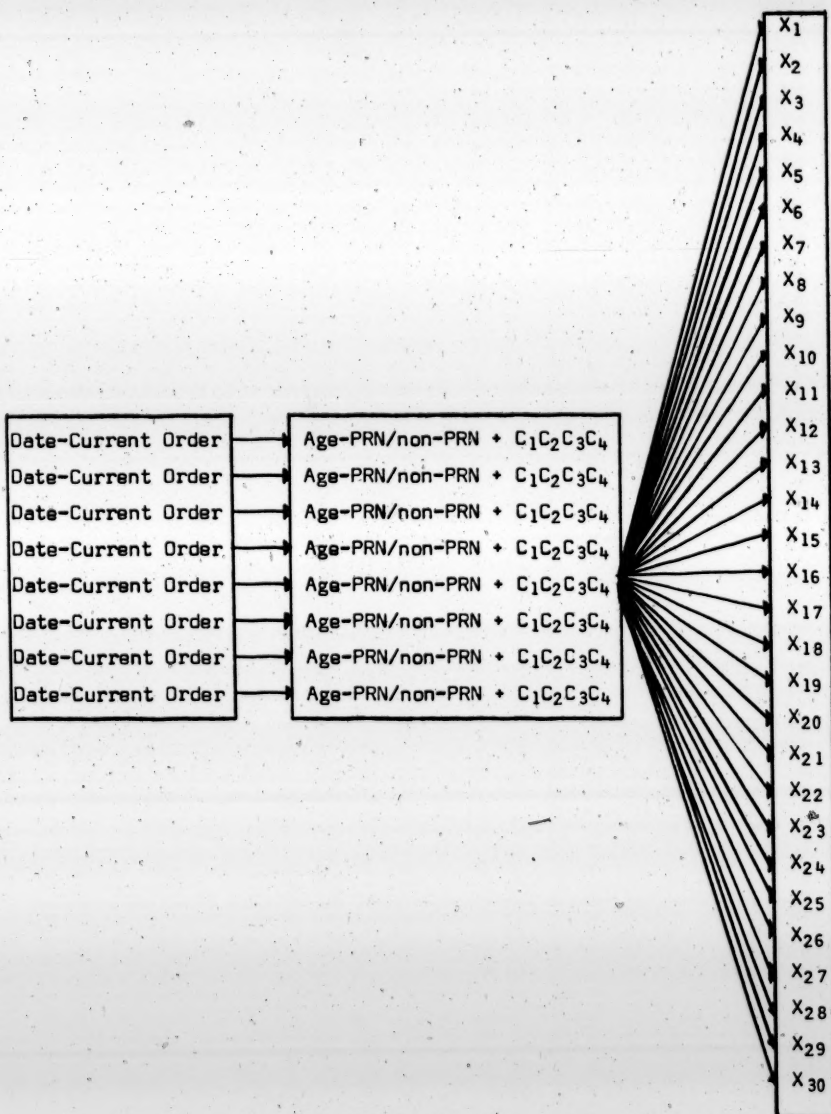
TABLE 4.5 Conversion From the Service Code Profile (example) to a Service Code Cluster Pattern

SERVICE CODE PROFILE	SERVICE CODE CLUSTER PATTERN	VARIABLE NUMBER	VARIABLE NAME	UTILITY
	1	X ₁	Nursing (Intensity 1, Intensity 3)	High
C 1317	0	X ₂	Nursing (Intensity 1, Intensity 3)	Moderate
	1	X ₃	Nursing (Intensity 5)	High
3 1317	0	X ₄	Nursing (Intensity 5)	Moderate
	0	X ₅	Nursing (Intensity 7)	High
1 3327	0	X ₆	Nursing (Intensity 7)	Moderate
	1	X ₇	Medications (Intensity 1, IV Intensity 3)	High
1 7327	0	X ₈	Medications (Intensity 1, IV Intensity 3)	Moderate
	0	X ₉	Medications (Intensity 3 IM & PO, Intensity 5)	High
A 3317	0	X ₁₀	Medications (Intensity 3 IM & PO, Intensity 5) Non-PRN	Moderate
	1	X ₁₁	Medications (Intensity 3 IM & PO, Intensity 5)	High
S 9242	0	X ₁₂	Medications (Intensity 3 IM & PO, Intensity 5) PRN	Moderate
	0	X ₁₃	Medications (Intensity 7)	High
S 9242	1	X ₁₄	Medications (Intensity 7)	Moderate
	0	X ₁₅	Ancillary Diagnostic (Intensities 1, 3, 5)	High
S 9242	0	X ₁₆	Ancillary Diagnostic (Intensities 1, 3, 5)	Moderate
	0	X ₁₇	Ancillary Diagnostic (Intensity 7)	High
W 9142	0	X ₁₈	Ancillary Diagnostic (Intensity 7)	Moderate
	1	X ₁₉	Ancillary Diagnostic (Intensity 9)	High
C 5323	0	X ₂₀	Ancillary Diagnostic (Intensity 9)	Moderate
	0	X ₂₁	Ancillary Therapeutic (Intensity 1)	High
B 9320	0	X ₂₂	Ancillary Therapeutic (Intensity 1)	Moderate
	0	X ₂₃	Ancillary Therapeutic (Intensity 3, Intensity 5)	High
A 3321	0	X ₂₄	Ancillary Therapeutic (Intensity 3, Intensity 5)	Moderate
	0	X ₂₅	Ancillary Therapeutic (Intensity 7, Intensity 9)	High
B 5323	0	X ₂₆	Ancillary Therapeutic (Intensity 7, Intensity 9)	Moderate
	0	X ₂₇	Hospital Based Service	
B 5323	0	X ₂₈	Discharge Planning Service	
	0	X ₂₉	Physician Rendered Service (Intensities 1,3)	Constant
A 5321	0	X ₃₀	Physician Rendered Service (Intensities 5,7,9)	Constant

appropriately utilized acute hospital patient day. The "ability to describe" was the criterion for rule acceptance.

A binary variable for each service code cluster was thus created to represent the presence or absence of each combination. By applying the rule to a coded medical services profile, a service code cluster pattern can be derived. The service code cluster pattern is the complete set of possible clusters of service codes used to describe each patient day. Figure 4.1 is the schematic representation of the classification and clustering process. Each service code cluster is a potential predictor variable in the level of care decision model.

CURRENT ORDERS	CODED MEDICAL SERVICES	SERVICE CODE CLUSTER PATTERN
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SCHEMATIC REPRESENTATION OF CONVERSION FROM
 FIGURE 4.1 CURRENT ORDERS TO SERVICE CODE CLUSTER PATTERN

NOTES

1. U.S. Department of Health, Education, and Welfare, International Classification of Diseases. Eighth Revision, Washington, D.C., 1968.
2. Miller, G.A. "The Magical Numbers Seven Plus or Minus Two. Some Limits on Our Capacity for Processing Information." Psychological Review, 63:81, 1957.
3. Feinstein, A.R. Clinical Judgment. Baltimore: Williams & Wilkins Co., 1976.
4. Patterson, G.W. "What is a Code?" Communications of the ACM, 3:315, 1960.
5. Kent, A. Information Analysis and Retrieval. New York: John Wiley & Sons, Inc., 1962.
6. Ball, G.H. Classification Analysis. Stanford Research Institute, Menlo Park, California, 1970.
7. Holloway, D.C.; Restuccia, J.D.; Goldberg, G.A.; and Fuhrer, R. "Determining the Appropriate Level of Care for Patients." Proceedings of a Forum on Measures of Quality of Care, Richmond, Va.; National Cooperative Services Center for Hospital Management Engineering, August, 1975.
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CHAPTER V RESULTSV.0 Introduction

A description of the study sample is presented first, including the findings on the information sources actually used for decision making. Reliability of decision making between nurses and between physicians, as well as predictive validity of the nurses' judgments is established, followed by a discussion of the development of a discriminant model based on data that is reliable and valid for the decision process under study. Then, the results of comparing the information provided by the discriminant model - L.O.C.I. - and the L.O.S. selector model are presented, thereby providing an evaluation of the models.

V.1 Description of the Sample

Although the sampling period started in June, an observed lack of consistency in the nurse's decision making necessitated rejecting the data from the first two months. The data base used for model development and evaluation consisted of 1072 observations representing 488 different patients. Table 5.1 summarizes the breakdown of the total observations, both by nursing unit and estimation/evaluation sets. Table 5.2 summarizes the number and the proportion of observations in groups G_S = SELECT FOR REVIEW, and $G_{\bar{S}}$ = SELECT NOT FOR REVIEW for each set.

TABLE 5.1 Frequency of Observations By Unit and Estimation/Evaluation Sets

NURSING UNIT	ESTIMATION SET	EVALUATION SET	TOTAL PER UNIT
Medical 1	110	63	173
Medical 2	117	50	167
Urology/EENT	96	46	142
Orthopedics	165	83	248
Gynecology	81	37	118
Surgical 1	79	45	124
Surgical 2	67	33	100
TOTAL PER SET	715	357	1072

TABLE 5.2 Frequency of Observations By Group Assignment and Estimation/Evaluation Set

GROUP ASSIGNMENT	ESTIMATION SET	EVALUATION SET	TOTAL PER GROUP
SELECT FOR REVIEW (G_S)	392	198	590
SELECT NOT FOR REVIEW (G_S^c)	323	159	482
TOTAL PER SET	715	357	1072
G_S /TOTAL	.55	.55	.55
G_S^c /TOTAL	.45	.45	.45

The mean length of stay of the patients in the study is 10.5 days; the median (or 50th percentile) is 7 days; and the mode (or most frequent) is 5 days. Figure 5.1 illustrates the distribution of lengths of stay (the sixteen lengths of stay ≥ 34 days were categorized as 34 days for display purposes only). When using only computer-based information for decision making, 55% of the observations were assigned to the SELECT FOR REVIEW group, G_S . The URNC obtained further information to make a final decision for 353 out of these 590 observations in G_S . That is, she consulted the chart and/or other health personnel 33% of the time. When non-computer-based information was added, the confident level of care assignment became acute care hospital facility for 248 out of the 353 observations. Hence, 77% of the URNC decisions were based on information available in the computer-based medical record.

V.2 Evaluation of Inter-Reviewer Agreement on Level of Care Assignments

V.2.1 Inter-Nurse-Reviewer Reliability

The importance of establishing reliability has been discussed in Chapter III. Two nurse reviewers (URNC and NC) applied levels of care criteria to the sampled population and arrived at independent judgments on level of care assignments for each observation. If the degree of agreement between the nurse reviewers did not differ significantly from zero, as measured by Kappa (κ), then the nurses' decisions are not reliable and a meaningful model could not be developed from the data.

The notation which will be used to denote group assignments by

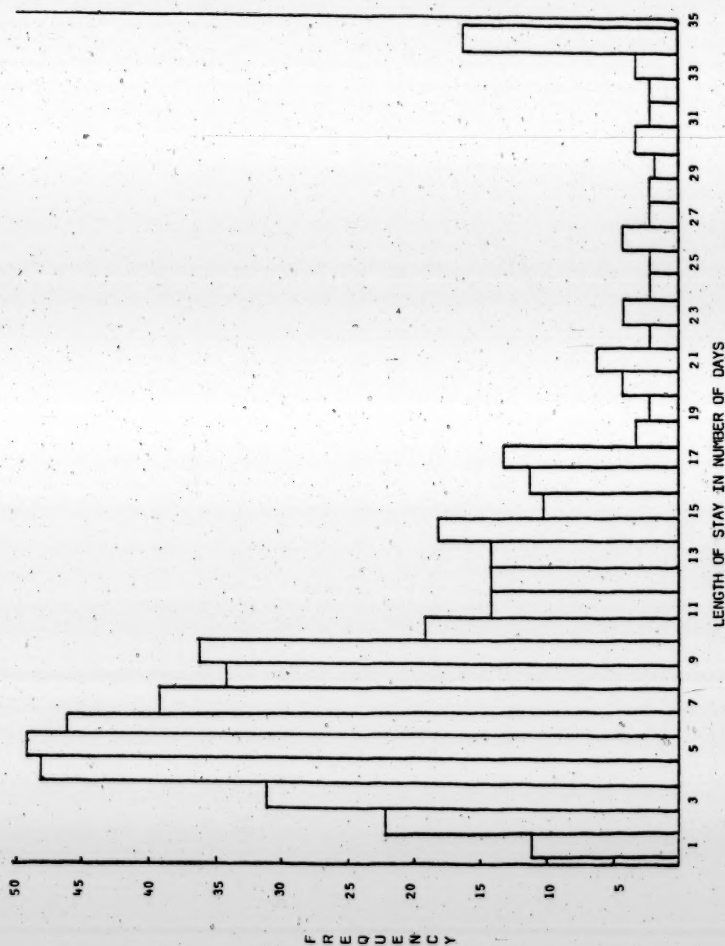


FIGURE 5.1 HISTOGRAM OF LENGTHS OF STAY FOR ENTIRE STUDY SAMPLE
(All lengths of stay (N=16) that were 2-34 were set equal to 34 for display only)

the nurse reviewers is as follows:

URNC: $G_{S,U} = \text{SELECT FOR REVIEW}$

$\bar{G}_{S,U} = \text{SELECT NOT FOR REVIEW}$

NC: $G_{S,N} = \text{SELECT FOR REVIEW}$

$\bar{G}_{S,N} = \text{SELECT NOT FOR REVIEW}$

The following hypothesis was tested:

H_0 : Inter Nurse Reviewer Reliability (Agreement) Equals Zero, $K_{NU} = 0$

The null hypothesis was tested three times: once each for the entire study sample (K_{NU}), for the estimation set ($K_{NU,E}$), and for the evaluation set ($K_{NU,T}$). Tables 5.3, 5.4 present the findings for the reliability assessment of the inter-nurse-reviewer assignments for the entire study sample, the estimation set and the evaluation set, respectively.

The Kappa's obtained for the study sample, estimation set and evaluation set are each significantly different from zero at the .01 level, i.e., the probability of obtaining this value of Kappa by chance alone is less than 1%. The null hypothesis therefore can be rejected, and we can state that there is inter-nurse-reviewer agreement. The nurses' assignments to the two groups are mutually consistent, i.e., the judgments are reliable. $K_{NU,E}$ and $K_{NU,T}$ were evaluated to ascertain that the separation into the two sets produced samples that were equivalent in reliability of judgments. Testing the difference between the two Kappas we obtain a $z = .309$ which is not significant at the .05 level, and the possibility that the two Kappas come from the same population cannot be rejected.

TABLE 5.3 Inter-Nurse-Reviewer Agreement Matrix for the Entire Study Sample

		URNC			
		$G_{S,U}$		$G_{S,U}$	
N U R S E C O D E R	$G_{S,N}$	531	$(p_{o,11} = .49)$ $(p_{e,11} = .31)$	59	$(p_{o,12} = .06)$ $(p_{e,12} = .24)$
		85	$(p_{o,21} = .08)$ $(p_{e,21} = .26)$	397	$(p_{o,22} = .37)$ $(p_{e,22} = .19)$
TOTAL		616	(.57)	456	(.43)
				TOTAL	
				1072	

Percent Agreement = 88%

 $K_{NU} = .727$ 99% Confidence Interval = .674 \leq $K_{NU} \leq$.781 $p > .01$

(In each cell ij , the upper left hand entry is the observed frequency, the upper right hand entry is the observed proportion, and the lower right hand entry is the chance or expected proportion. Subsequent agreement matrices will show only the frequencies and results.)

TABLE 5.4 Inter-Nurse-Reviewer Agreement Matrices for Estimation/Evaluation Sets

URNC

ESTIMATION SET				EVALUATION SET				
		$G_{S,U}$	$G_{S,U}^*$	TOTAL			TOTAL	
NURSE	$G_{S,N}$	352	40	392	$G_{S,N}$	179	19	198
	$G_{S,N}^*$	54	269	323		31	128	159
	TOTAL	406	309	715	TOTAL	210	147	357

Percent Agreement = 87%

$$K_{NU,E} = .734$$

99% Confidence Interval =

$$.688 \leq K_{NU,E} \leq .799$$

$$p < .01$$

Percent Agreement = 86%

$$K_{NU,T} = .714$$

99% Confidence Interval =

$$.620 \leq K_{NU,T} \leq .809$$

$$p < .01$$

$$z_{K_{NU,E}/K_{NU,T}} = .309 \quad (p > .05)$$

The reliability of nurse reviewer decision making is not very surprising. Both have training and experience in levels of care criteria and the rules for applying the criteria. Previous studies assessing the reliability of utilization review coordinators decisions arrived at the same conclusions.¹ Having established reliability in the nurse reviewers' judgments, the predictive validity of the decisions must be established. If the nurses agree with each other, but do not provide a valid screen for the utilization review physicians, they are not fulfilling their true function.

V.2.2 Predictive Validity of Nurse Reviewers' Judgments

An instrument used for prediction is evaluated by an established criterion of the behavior one is trying to predict. An objective "correct" answer for level of care assignment does not exist. Given that the level of care concept developed from progressive patient care principles which were then translated into legislative dictate, the only "correct" answer is the one agreed upon by PSRO physicians. Therefore, physicians' (with Utilization Review experience) judgments have been used as the criterion by which to evaluate the nurse reviewers' judgments. The stability of the criterion was established by the use of Kappa to measure the reliability of physicians' judgments.

V.2.2.a Inter-Physician Reviewer Reliability

The following notation will be used to denote the judgments of the physician reviewers:

TABLE 5.5 Inter-Physician-Reviewer Agreement Matrix

PHYSICIAN - 1		PHYSICIAN - 2	
$G_{S,P1}$	$G_{S,P1}$	$G_{S,P2}$	$G_{S,P2}$
51	17	68	
5	26	31	
56	43	99	

Percent Agreement = 78%

 $K_{PIP2} = .533$ 99% Confidence Interval = .311 \leq $K_{PIP2} \leq$.754 $p < .01$

Physician-1: $G_{S,P1} = \text{SELECT FOR REVIEW}$

$G_{\bar{S},P1} = \text{SELECT NOT FOR REVIEW}$

Physician-2: $G_{S,P2} = \text{SELECT FOR REVIEW}$

$G_{\bar{S},P2} = \text{SELECT NOT FOR REVIEW}$

The null hypothesis that is tested to establish reliability in physician level of care decision making is as follows:

H_0 : There Is No Physician Consensus on Level of Care Assignments,

$$K_{P1P2} = 0.$$

The physician level of care judgments and the measure of agreement are summarized in Table 5.5.

The physicians are reliable in their level of care assignments. K_{P1P2} is significantly different from zero at the .01 level and the null hypothesis is rejected. The degree of agreement between the physicians is not as high as between the nurses, K_{NU} K_{P1P2} . A substantial proportion of the disagreements is a consequence of marginal discrepancies. This discrepancy was investigated by reviewing the comments the physicians had been asked to record as they were making their decisions. Physician-2 frequently questioned the appropriateness of medical services which then affected his level of care decision. The physicians had been asked to make a utilization review decision, that of appropriateness of location based on medical services provided. The validity of using this assumption had been established by a previous study² which tested the hypothesis that the services ordered and used in determining the level of care were not unreasonable or inappropriate to the patients' medical care needs. Therefore, Physician-2 was making an unnecessary and biased decision in view of the objective. This

additional factor in arriving at a judgment resulted in Physician-2 assigning 12% more of the observations to $G_{S,P2}$ than assigned by Physician-1. Due to this consistent bias, and the fact that reliability of physicians' judgments had been established anyway, Physician-1's judgments were used as the criterion for a "correct" level of care assignment.

V.2.2.b Nurse-Physician Agreement

The following hypothesis tests the predictive validity of the URNC's judgments:

H_0 : There Is No Agreement on Level of Care Assignments Between Nurse and Physician Reviewers, $K_{NP} = 0$.

If the null hypothesis is rejected, it can be said that the nurse reviewers predict well the decisions that physician reviewers would arrive at. Therefore, they can act as physician representatives and screen patients for physician review. The degree of predictive validity is a function of the value of the coefficient of agreement which measures the correlation of categorical assignments between the instrument and the criterion. Table 5.6 summarizes the results of nurse-physician level of care judgments. (Since the nurse reviewers are considered reliable decision makers, one could choose the assignments of either one for (1) assessing the nurse-physician-reviewer agreement level and (2) developing the discriminant function.)

The K_{NP} is significant at the .01 level and the null hypothesis is rejected. It can be observed that the disagreements that occur are usually in the case of the nurse reviewer assigning observations to the

TABLE 5.6 Nurse Coder-Physician - 1 Agreement Matrix

NURSE C O D D E R		PHYSICIAN - 1	
$G_{S,N}$	$G_{S,P1}$	$G_{S,P1}$	TOTAL
50	13	63	
6	30	36	
TOTAL	56	43	99

Percent Agreement = 81%

 $K_{NP} = .602$ 99% Confidence Interval = $.396 \leq K_{NP} \leq .808$ $p < .01$

SELECT FOR REVIEW group that the physician judges as appropriate, i.e., False Positives. In view of the intent of the selector system, an acceptable proportion of False Positives is not as serious as False Negatives. The predictive validity of the nurse reviewers' judgments is highly satisfactory; she is a good predictor of those cases the URMD would want selected for further review and those which can be considered appropriate.

V.2.3 Summary of Reliability and Validity Results

Nurse reviewer reliability and predictive validity have been established. Having done so, we can assume that observations which will be used to determine a discriminant function have been assigned in a consistent fashion and satisfy the intent of the assignment procedure. This assumption is important since the accuracy level of the discriminant function is related to the accuracy with which the observations were originally assigned. Given that an absolute "correct" answer does not exist, the coefficients of agreement are high enough to permit confidence in the data base.

V.3 A Discriminant Model for Level of Care Allocation

A pattern of 30 binary variables has been established to represent the various types of medical services used in making level of care assignments. A stepwise linear discriminant analysis program³ was used to determine which of the binary variables are most useful in discriminating SELECT FOR REVIEW from SELECT NOT FOR REVIEW observations.

Nine variables were chosen and are listed in Table 5.7. The results at each step of the stepwise linear discriminant analysis program are included in Appendix C.

The F-values for inclusion of variables X_{20} and X_{26} are low. The classification matrix of the linear discriminant analysis program after Step 7 is almost identical to the classification matrix after Step 9. Given that the goal is to use the smallest subset of variables which achieve a desired level of discriminating ability, the incremental discriminating value of these two variables was questioned. Therefore, a logistic discriminant function was fit using the first seven variables selected by the stepwise linear discriminant function, as well as for all nine recommended variables. The accuracy of allocation for the seven-variable and nine-variable logistic functions were equivalent. Since there is no improvement in discrimination powers with variables X_{20} and X_{26} included in the model, and an objective is to determine the smallest subset of variables to discriminate satisfactorily, the seven-variable-model was chosen for evaluation. (See Appendix D for results of fitting logistic function using seven variables.)

The logistic discriminant function was developed from the estimation set and tested on the evaluation set. The coefficients were calculated by the maximum likelihood method.⁴ A Logit of p is calculated for each observation, and is the Level of Care Index. The value of the L.O.C.I. is used to allocate an observation to one of the two groups, \hat{G}_S or $\hat{G}_{\bar{S}}$. The L.O.C.I. is calculated by the following equation:

TABLE 5.7 Optimal Discriminators for Level of Care Allocations

VARIABLE NUMBER	VARIABLE NAME	UTILITY	F-VALUE FOR INCLUSION
X ₁	Nursing (Intensity 1, Intensity 3)	High	31.76
X ₃	Nursing (Intensity 5)	High	51.28
X ₇	Medications (Intensity 1, IV Intensity 3)	High	111.19
X ₁₁	Medications (Intensity 3 IM & PO, Intensity 5) PRN	High	25.85
X ₁₇	Ancillary Diagnostic (Intensity 7)	High	18.65
X ₁₉	Ancillary Diagnostic (Intensity 9)	High	10.39
X ₂₇	Hospital Based Service		70.32
* X ₂₀	Ancillary Diagnostic (Intensity 9)	Moderate	6.78
* X ₂₆	Ancillary Therapeutic (Intensity 7, Intensity 9)	Moderate	5.09

* Variables not included in seven-variable model

$$L.O.C.I. = \ln\left(\frac{p}{1-p}\right) = -.942 + .907X_1 + .601X_3 + .848X_7 + .573X_{11} \\ + .551X_{17} + .349X_{19} + 1.763X_{27}$$

where a value for L.O.C.I. less than zero suggests possible misutilization of an acute care hospital facility, and the observation is then allocated to \hat{G}_S . (see Appendix E for individual results.) Inspection of the coefficients indicates that with the exception of variable X_{27} (the hospital based service variable) at least two and sometimes three variables must be present to allocate an observation to \hat{G}_S . The coefficients represent the weight or amount of increase in L.O.C.I. caused by the presence of the corresponding variable. In addition, the estimate of the posterior probability p can be calculated. Thus, for example; a patient receiving variable X_1 only, would have a L.O.C.I. = .035, and would be allocated to \hat{G}_S with a $\Pr(G_S | X_1) = .52^*$. If another patient had additional service codes denoted by variable X_7 , the L.O.C.I. would = + .813, and the patient would be allocated to \hat{G}_S with a $\Pr(G_S | X_1 X_7) = .84^*$. The additional variable, increased the probability that the patient required an acute hospital from .48 to .84. The results of fitting the logistic discriminant function using the estimation set are summarized in Table 5.8.

* The logistic discriminant program used in this research sets

$$Y = \frac{1}{2} \ln\left(\frac{p}{1-p}\right) \text{ which only affects the range of } p \text{ values.}$$

TABLE 5.8 L.O.C.I. Allocation Matrix for Estimation Set

		NURSE		TOTAL
		G_S	$G_{\bar{S}}$	
L.O.C.I.	\hat{G}_S	338	106	444
	$\hat{G}_{\bar{S}}$	54	217	271
TOTAL		392	323	715

Correct Allocation Rate = 78%

TABLE 5.8 L.O.C.I. Allocation Matrix for Estimation Set

		NURSE		TOTAL
		G_S	$G_{\bar{S}}$	
		\bar{G}_S	$\bar{G}_{\bar{S}}$	
L. O. C. I.		338	106	444
		54	217	271
TOTAL		392	323	715

Correct Allocation Rate = 78%

The misclassification rate for the estimation set is 22%.

Norusis and Jacquez state that a probability of correct classification in the range of 80% is often acceptable to many investigators when the groups are not clearly defined. In a population where the groups are clearly differentiable, a higher correct classification rate would be sought. Level of care assignments are a function of various cut-off points on a continuum of medical service needs. Observations at either end of the continuum are easily differentiated, however many observations fluctuate around the middle of the continuum and therefore are more difficult to decide upon. These are also the observations upon which the reviewers tended to disagree.

Since the objective was to see if a L.O.C.I. capturing the reviewers judgments could be developed, and if one could, whether it would predict more accurately than L.O.S. which observations to review, model development was suspended in order to perform the comparative evaluation. If the L.O.C.I. was considered a better predictor than the L.O.S. selector model, then one can only assume that further development work would only enhance its discriminating abilities.

V.4 Comparative Evaluation of L.O.C.I. and L.O.S.

The effectiveness of each of the models is a function of correct allocation rate, sensitivity, specificity, and outcome analysis. The degree to which the model (L.O.C.I.) approximates the reviewers' judgments is described by the correct allocation rate. The results of applying L.O.C.I. to the entire evaluation set are presented first. However, having documented only the length of stay guidelines for the

50th and 75th percentile, and not those for the 90th, a bias in favor of L.O.C.I. would be introduced when comparing the two selector models. This is due to the fact that observations eligible for assessment by L.O.C.I. are no longer eligible for L.O.S. if the actual length of stay is beyond the 75th percentile for the current diagnosis or surgery (when assigning the length of stay diagnosis current is defined as the diagnosis entered in the computer system at the time of review). Therefore, all subsequent evaluation results are for the subset of the evaluation set whose actual length of stay was less than or equal to the 75th percentile of their current diagnosis. The evaluations were conducted for the current diagnosis and the discharge diagnosis separately. This was done because of the high percentage of change between admit and discharge diagnoses as is presented in Table 5.9. The accuracy of the information used in either model affects the accuracy of the predictions. Thus, if by using length of stay guidelines for discharge diagnoses a better selector model was found, then greater emphasis might be placed on entering the primary diagnoses as early as possible or changing the guidelines to reflect the admitting diagnosis. As a result, 71% and 75% of the observations in the evaluation set were included for evaluation when the cut-off was the 75th percentile by the current and discharge diagnoses, respectively.

V.4.1 Evaluation of L.O.C.I. Allocations Pre and Post the 75th Percentile

The comparative evaluation of L.O.C.I. and L.O.S. will be performed for the subsets of the evaluation set which include only those

TABLE 5.9 Comparison of Admit and Discharge Diagnostic and Length of Stay Information

	FREQUENCY	PROPORTION OF STUDY PATIENTS	PROPORTION OF PATIENTS WITH ADMIT D _x ≠ DISCHARGE D _x
Admit D _x ≠ Discharge D _x	229	.47	
50th Percentile LOS Differs	169	.35	.74
Provisional D _x			
Medically	97	.20	.42
Symptoms			
Lab Result			
Very Different	15	.03	.07
Other			
Primary D _x /Procedure	86	.18	.38
Entered in MIS			
50th Percentile LOS Change when	81	.17	.35
Primary Entered in MIS			

observations whose length of stay is equal to or less than the 75th percentile of the current and discharge diagnoses. It was desirable to confirm whether L.O.C.I. has equivalent discriminating ability before and after the 75th percentile for either diagnosis.

The chi-square (χ^2) test⁶ was used to compare allocation matrices pre and post the 75th percentile. The χ^2 test is a method of comparing the proportions of two samples. It permits testing the null hypothesis that there is no relationship between the model's allocations and the pre and post 75th percentile subsets, that is, that the accuracy of allocations is independent of the actual length of stay relative to the length of stay norms.

Tables 5.10 and 5.11 are the contingency tables representing the allocation matrices for the pre and post 75th percentile subsets for both current and discharge diagnoses. The χ^2 obtained are highly significant and the null hypotheses are rejected. The allocations are not independent of the patient's length of stay relative to the norm, neither using current nor discharge diagnosis. If each group is examined separately, that is looking at G_S separately from $G_{\bar{S}}$, the $\chi^2 = .39$ (1.32)*, $p > .05$ found for G_S , does not permit the rejection of the null hypothesis, whereas $\chi^2 = 12.49$ (13.78)*, $p < .01$, for $G_{\bar{S}}$ does. This can be interpreted as indicating that L.O.C.I. selects patients for review who should be reviewed equally well before and after the 75th percentile (for either diagnosis), however, for patients who need not be

* Results in parentheses are for subset defined by discharge diagnosis.

TABLE 5.10 Pre/Post 75th Percentile Subset Contingency Tables for Current Diagnosis

	L.O.C.I.			
	TP	FN	FP	TN
Pre 75th Percentile	112	14	29	97
Post 75th Percentile	66	6	18	15

$$\chi^2 = 20.67 \quad d.f. = 3, \quad p < .005$$

NURSE SELECT FOR REVIEW	L.O.C.I.			
	\bar{G}_S	\bar{G}_S	\bar{G}_S	\bar{G}_S
Pre 75th Percentile	112	14		
Post 75th Percentile	66	6		

$$\chi^2 = 0.39 \quad d.f. = 1, \quad p > .05$$

NURSE SELECT NOT FOR REVIEW	L.O.C.I.			
	\bar{G}_S	\bar{G}_S	\bar{G}_S	\bar{G}_S
Pre 75th Percentile	29	97		
Post 75th Percentile	18	15		

$$\chi^2 = 12.49 \quad d.f. = 1, \quad p < .005$$

TABLE 5.11 Pre/Post 75th Percentile Subset Contingency Tables for Discharge Diagnosis

	L.O.C.I.			
	TP	FN	FP	TN
Pre 75th Percentile	120	16	31	101
Post 75th Percentile	58	4	16	11
	$\chi^2 = 21.58$ d.f. = 3, $p < .005$			

NURSE SELECT FOR REVIEW	L.O.C.I.		\hat{G}_S	$\hat{G}_{\bar{S}}$
	Pre 75th Percentile	120	16	
	Post 75th Percentile	58	4	
	G_S	$\chi^2 = 1.32$ d.f. = 1, $p > .05$		

NURSE SELECT NOT FOR REVIEW	L.O.C.I.		\hat{G}_S	$\hat{G}_{\bar{S}}$
	Pre 75th Percentile	31	101	
	Post 75th Percentile	16	11	
	$G_{\bar{S}}$	$\chi^2 = 13.78$ d.f. = 1, $p < .005$		

TABLE 5.11 continued

MEASURES OF PERFORMANCE

<u>Pre 75th Percentile</u>	<u>Post 75th Percentile</u>
Correct Allocation Rate = 82%	Correct Allocation Rate = 78%
Selector Sensitivity = .88	Selector Sensitivity = .94
Selector Specificity = .77	Selector Specificity = .41
Predictive Sensitivity = .80	Predictive Sensitivity = .78
Predictive Specificity = .86	Predictive Specificity = .73

selected, there is a difference in L.O.C.I.'s discriminating powers between the subsets. The effects of these differences will be discussed in terms of the effects on the measures of performance.

Tables 5.12 and 5.13 present the allocation matrices for the evaluation set, for the above defined subsets, as well as summarizing the measures of performance for each.

The Correct Allocation Rate decreases several percentage points in the post 75th percentile subset. The selector sensitivity increases slightly, and the predictive sensitivity remains constant. This latter result is important because it indicates that the predictive value of a L.O.C.I. selected patient is equivalent pre and post the 75th percentile cut-off. A patient selected for review by L.O.C.I. has approximately an 80% probability of requiring further review in either subset. However, the specificity levels of L.O.C.I. are affected by the patient's actual length of stay. The selector specificity, as well as predictive specificity, of L.O.C.I. are lower in the post 75th percentile subset. The predictive specificity decreases about 15%, but the selector specificity difference of 33% demonstrates the rapidly decreasing quality of L.O.C.I. after the 75th percentile for this criterion. It selects far more patients for review as the patient's length of stay increases. This factor is not surprising, as one would expect that the service code patterns of appropriately located patients in this subset are not very different from patients needing further review and therefore are more difficult to differentiate. Keeping in mind the intent of the selector model, errors of this type are still preferable. However, because the statistical significance of these differences cannot be

TABLE 5.12 L.O.C.I. and L.O.S. Allocation Matrices for Pre 75th Percentile Evaluation Subset (CURRENT D_x)

		NURSE			
		\bar{G}_S	$\bar{G}_{\bar{S}}$	TOTAL	
\bar{G}_S	L. O. C. I.	112	29	141	\bar{G}_S
		14	97	111	
TOTAL		126	126	252	TOTAL

		\bar{G}_S	$\bar{G}_{\bar{S}}$	TOTAL	
\bar{G}_S	L. O. S.	27	17	44	\bar{G}_S
		99	109	208	
		TOTAL	126	126	252

Correct Allocation Rate = 83%

Selector Sensitivity = .89

Selector Specificity = .77

Predictive Sensitivity = .79

Predictive Specificity = .87

Correct Allocation Rate = 54%

Selector Sensitivity = .21

Selector Specificity = .87

Predictive Sensitivity = .61

Predictive Specificity = .52

TABLE 5.13 L.O.C.I. and L.O.S. Allocation Matrices for Pre 75th Percentile Evaluation Subset (DISCHARGE Dx)

		NURSE			
		\hat{G}_S	$\hat{G}_{\bar{S}}$	TOTAL	
\hat{G}_S	L. O. C. I.	120	31	151	\hat{G}_S
		16	101	117	
TOTAL		136	132	268	TOTAL
$\hat{G}_{\bar{S}}$	L. O. S.	28	16	44	$\hat{G}_{\bar{S}}$
		108	116	224	
		136	132	268	TOTAL

Correct Allocation Rate = 82%

Selector Sensitivity = .88

Selector Specificity = .77

Predictive Sensitivity = .80

Predictive Specificity = .86

Correct Allocation Rate = 54%

Selector Sensitivity = .21

Selector Specificity = .88

Predictive Sensitivity = .64

Predictive Specificity = .52

determined, any subsequent assertions that are stated about L.O.C.I. will be for the pre 75th percentile subset of the evaluation set and will not necessarily hold true for L.O.C.I.'s abilities at any point in a patient's hospitalization. The results are equivalent whether the subset is defined by the current or the discharge diagnosis.

V.4.2 Comparison of the Correct Allocation Rates of the Selector Models

The Correct Allocation Rate is a measure of the accuracy of a selector model. The Correct Allocation Rate for L.O.C.I. is 83% and for L.O.S. it is 54% indicating that L.O.C.I. is more accurate in its allocations. Because fewer days are eligible when using L.O.S., this model selects a smaller total proportion of cases, a factor which can affect its accuracy. Therefore, the results of the sensitivity and specificity analysis will aid in interpreting the importance of the accuracy difference between the models. L.O.S._C and L.O.S._D refer to the length of stay selector models using the current and discharge diagnoses, respectively.

V.4.3 Selector Sensitivity of Models

The proportion of True Positives, $\Pr(\hat{G}_S | G_S)$, is a measure of selector sensitivity. Although correction for chance is not included, a simple comparison of the selector sensitivity of two tests, or as in this case models, provides an indication of the increased sensitivity of one

test over the other:

Selector Sensitivity_{L.O.C.I.} = .89

Selector Sensitivity_{L.O.S./C} = .21

Selector Sensitivity_{L.O.S./D} = .21

By the use of this measure we conclude that L.O.C.I. is considerably more sensitive in selecting cases for review. For the observations the URNC considered as needing further review, L.O.C.I. would have selected 89% and L.O.S. would select 21%. All observations in the set are eligible for selection by L.O.C.I., whereas L.O.S. can only select 18%. By chance alone, L.O.C.I. could be more sensitive. When comparing L.O.C.I. for only L.O.S. selected cases we find that the selector sensitivity of L.O.C.I. = .93. This result further amplifies the selector sensitivity level of L.O.C.I. in that almost all (25 out of 27) the True Positives in this group would have been selected by L.O.C.I. Of the 79% that L.O.S. would have missed, 88% would have been selected by L.O.C.I.

V.4.4 Selector Specificity of Models

The proportion of True Negatives, $\Pr(\hat{G}_S | G_S)$ is a measure of selector specificity. The selector specificity reflects a model's discriminating powers. It indicates the model's error rate for observations not necessitating further review. If the selector specificity level is low then too many patients would be reviewed unnecessarily which eliminates the value of having a selection process.

Selector Specificity_{L.O.C.I.} = .77

Selector Specificity_{L.O.S./C} = .87

Selector Specificity_{L.O.S./D} = .88

The results demonstrate that L.O.S. is more specific than L.O.C.I. Again, this is due in part to the proportion of cases which are eligible for selection by each method. However, when the selector specificity of L.O.C.I. is calculated for L.O.S. selected cases, it is found to be 88%. For both selector models, the selector specificity levels are fairly high, a factor necessary for a selection process.

V.4.5 Predictive Sensitivity and Specificity of Selector Models

Selector sensitivity and specificity assess the performance of the models, i.e., how good is the selection process. The predictive sensitivity and specificity are a reorganization of the data to assess the value of the information provided by the models. The informational value of both positive and negative responses by the selector model are important to evaluating the models' errors. As already stated, these two measures are related to the selector sensitivity and specificity, however they are not as dependent on the proportion of cases eligible for selection.

Predictive Sensitivity_{L.O.C.I.} = .79

Predictive Sensitivity_{L.O.S./C} = .61

Predictive Sensitivity_{L.O.S./D} = .64

Predictive Specificity_{L.O.C.I.} = .87

Predictive Specificity_{L.O.S./C} = .52

Predictive Specificity_{L.O.S./D} = .52

The predictive value of L.O.C.I. exceeds that of L.O.S. for both positive and negative responses. A patient selected for review by L.O.C.I. has a higher probability of needing further review than a patient selected by L.O.S. Furthermore, patients not selected for review by L.O.C.I. have a higher probability of not needing further review than those not selected by L.O.S.

V.4.6 Summary of Comparison of L.O.C.I. and L.O.S.

The acceptable levels of sensitivity and specificity are dependent upon the intended use of the test or model. If the action associated with a positive result is costly (in time, risk, money, etc.) then high specificity is sought. If the outcome of a False Negative result is costly then sensitivity is maximized. Keeping the objective of Utilization Review and a selector model in mind, minimization of False Negatives with an acceptable level of False Positives would be the criterion for choosing a model. Assuming equal costs of errors, choosing the maximum accuracy rate is a means of considering both sensitivity and specificity; alternatively, the model with maximum predictive value of information can be the criterion for choice. If unequal costs should be assumed, allocation errors or the specificity/sensitivity tradeoffs can be weighted in calculating a criterion score.

When both selector sensitivity and selector specificity are taken

into consideration, L.O.C.I. is preferable to L.O.S. for selecting cases for the URNC. L.O.C.I. is far more sensitive and L.O.S. is only somewhat more specific. When the predictive value of the information provided by the models is considered, the preference for L.O.C.I. increases. Table 5.14 summarizes the findings of the evaluation of L.O.C.I. and L.O.S. Results are comparable for L.O.S. using either the current or discharge diagnosis.

A modification of the proposed models still yields comparable results. When patients who had a discharge order written were deleted from the evaluation set, the accuracy level was 80% and 52% for L.O.C.I. and L.O.S., respectively. Patients who have a discharge order could appear on a separate list for verification of discharge and reason for order not being carried out when that is the case. For a system using L.O.C.I., patients who are considered appropriate in the acute hospital or for L.O.S., patients who are pre 50th percentile, and who have a discharge order, should be verified to ensure that the patient is not being discharged prematurely.

V.5 Outcome Analysis

It has just been demonstrated that L.O.C.I. has greater predictive informational value than L.O.S., that L.O.C.I. has far more selector sensitivity than L.O.S., but that L.O.S. is somewhat superior in selector specificity. These results were found when the criterion was the URNC judgment based on the computer medical record.

For the entire study sample, the URNC sought information in addition to that provided by MIS 33% of the time before making a final

TABLE 5.14 Summary of Comparative Evaluation of L.O.C.I. and L.O.S. Selector Models

	L.O.C.I.C	L.O.S.C	L.O.C.I.D	L.O.S.D
NURSE - SELECT FOR REVIEW $Pr(\hat{G}_S)$.50	.50	.51	.51
MODEL - SELECT FOR REVIEW $Pr(\hat{G}_S)$.56	.18	.55	.16
Difference	-.06	.32	-.04	.35
SELECTOR SENSITIVITY $Pr(\hat{G}_S G_S)$.89	.21	.88	.21
SELECTOR SPECIFICITY $Pr(\hat{G}_S^c G_S^c)$.77	.87	.77	.88
PREDICTIVE SENSITIVITY $Pr(G_S \hat{G}_S)$.79	.61	.80	.64
PREDICTIVE SPECIFICITY $Pr(G_S^c \hat{G}_S^c)$.87	.52	.86	.52
CORRECT ALLOCATION RATE	83%	54%	82%	54%

decision. In the subset of the evaluation set, she continued beyond MIS in the information acquisition sequence 25% of the time. When she added non-computer-based information, a total of 67% of the observations were considered to be appropriately located in the acute care hospital. Thus, for 83% of the subset, the URNC made a decision using computer-based information. Are the measures of performance affected by the 17% change in the URNC's decisions? In view of the comparable results for L.O.S._C and L.O.S._D, the outcome analysis was conducted only for L.O.S._C.

The outcome has been defined as the "confident" decision. When the URNC considers a patient as "APPROPRIATE" she takes no further action. When she considers the patient as "INAPPROPRIATE", she may take any of a number of different actions, including no action, but with documented explanation. Hence, all "confident" decisions are that the observation is either "APPROPRIATE" or "INAPPROPRIATE" in the acute hospital. The results of the outcome analysis are summarized in Table 5.15.

The selector sensitivity levels of L.O.C.I. and L.O.S. did not change for the "confident" decisions. The selector specificity of L.O.C.I. decreased to 60%, whereas it only decreased to 85% for L.O.S. This indicates that L.O.C.I. selects more patients for review that the URNC considers "APPROPRIATE" when all available patient information is used. However, if we deduct the patients that L.O.C.I. selected that the URNC arrived at a "confident" decision using computer-based information - she could quickly review the selected patients by the use of MIS - the selector specificity level increases to 81%.

TABLE 5.15 Outcome Analysis of L.O.C.I. and L.O.S. Allocations

NURSE			
		"INAPPROPRIATE"	"APPROPRIATE" TOTAL
L. O. C. I.	\bar{G}_S	74	67
	$\bar{G}_{\bar{S}}$	9	102
TOTAL		83	169
		TOTAL	
		19	26
		64	143
		83	169
		TOTAL	
		45	207
		207	252

Correct Allocation Rate = 70%

Selector Sensitivity = .89

Selector Specificity = .60

Predictive Sensitivity = .53

Predictive Specificity = .92

Correct Allocation Rate = 64%

Selector Sensitivity = .23

Selector Specificity = .85

Predictive Sensitivity = .42

Predictive Specificity = .69

When non-computer-based information is added, the predictive value of a positive response decreases for both L.O.C.I. and L.O.S., however, it remains greater for L.O.C.I. The predictive value of a negative response increases for both models, but for L.O.C.I. it is much higher. If L.O.C.I. does not select a patient for review, there is a 92% probability that the patient is truly appropriate. In view of the objective of maintaining delegated status, this result is highly satisfactory.

V.6 Summary

The outcome analysis produced results that are very similar to those found in the evaluation of the models for approximating a decision using computer-based information only. L.O.C.I. allocations have a higher probability of being correct. For a utilization review selector model, missing patients who should be reviewed is more serious than unnecessarily reviewing an appropriately located patient. Of course, there is a tradeoff between the two types of errors and the tradeoff ratio must be considered. L.O.S. misses 78% of the patients it should review against L.O.C.I. missing 11%, which may be far more serious than the 40% which would be unnecessarily reviewed if using L.O.C.I. versus the 15% erroneously selected by L.O.S.

When evaluating the information provided by the models, L.O.C.I. is superior in predictive value. However, it must be remembered that its value is relative to the actions which are taken as a result of having or not having the information.

NOTES

1. Kever, C. "Utilization Review Coordinators Reliability Study." Unpublished Paper. Hospital Utilization Review Study. University of California School of Public Health, Berkeley, California, June, 1975.
2. Holloway, D.C.; Restuccia, J.D.; Goldberg, G.A.; and Fuhrer, R. "Determining the Appropriate Level of Care for Patients." Proceedings of a Forum on Measures of Quality of Care, Richmond, Va.: National Cooperative Services Center for Hospital Management Engineering, August, 1975.
3. BMDP7M is the linear discriminant program used for variable selection.
Dixon, W.J. BMD, Biomedical Computer Programs, Berkeley, California: University of California Press, 1975.
4. Program used for determination of the logistic discriminant function.
Clayton, D. Quantal Regression Program. London School of Hygiene and Tropical Medicine, 1969.
5. Norusis, M.J. and Jacquez, J.A. "Diagnosis. I. Symptom Nonindependence in Mathematical Models for Diagnosis." Computers and Biomedical Research, 8:156, 1975.
6. Snedecor, G.W. and Cochran, W.G. Statistical Methods. Ames, Iowa: Iowa State University Press, 6th Edition, 1967.
The χ^2 Test is a method for comparing the proportions in two or more groups, that is, evaluating if two or more groups have comparable proportions of the criterion variables.
 χ^2 is calculated by:

$$\chi^2 = \sum \frac{(f - F)^2}{F}$$

where f is the observed cell frequency
F is the expected cell frequency
m is the number of cells

CHAPTER VI CONCLUSIONSVI.0 Introduction

The PSRO program requires the review of hospitalized patients to assure the appropriate utilization of health care services while ensuring the quality of care.¹ The selection of patients for review has been the subject of this study. To ascertain if the selection process could be improved, this dissertation proposed to investigate three hypotheses:

Hypothesis 1: Patients who may be inappropriately located in an acute hospital are characterized by a medical services profile (i.e. current orders) which differs from that of patients who are probably appropriately located.

Hypothesis 2: Inappropriate utilization is more accurately predicted by a level of care index (L.O.C.I.) than by length of stay by diagnosis (L.O.S.).

Hypothesis 3: When non-computer based information is added, probable inappropriate location is more accurately predicted by a level of care selector model than by a length of stay selector model.

The results of this experiment have demonstrated that the patients who are appropriately located in an acute hospital do have different medical services profiles from those patients who are not appropriately located. A computerized decision model using the medical services profile as a set of predictor variables can discriminate between those patients who may need to be in an acute hospital and those who may not with an 81% level of accuracy. The computerized decision model is an index of the level of care needed by a patient, and can serve as a selector model for Utilization Review. This computerized index of level of care is a more valid predictor for a Utilization Review Coordinator than the length of stay norms. Not only is the level of care index superior to the length of stay norms at selecting the patients the URNC would want to have selected for further review, but its performance remains comparable at predicting the confident decision --- the decision prompting feedback for corrective action. Stated otherwise, the level of care index is better at predicting the URNC's confident decisions, i.e., the patients who are "APPROPRIATE" (probably appropriately located) and "INAPPROPRIATE" (probably inappropriately located).

Therefore, it can be stated that inappropriate utilization is more accurately predicted by the level of care index developed in this study, than by the length of stay selector model proposed by the Professional Standards Review Organizations.

Health care experts defined a pattern of 30 clusters of medical services capable of describing a patient day in terms of current orders. Seven clusters of medical services were found to be useful predictors of

appropriate utilization. They are listed in Table 6.1 in descending order of discriminating powers based on the order the variables were selected by a stepwise linear discriminant analysis.

A discriminant function which is the sum of these weighted variables was empirically determined by a Logistic Discriminant Method and can predict which patients to select with an 81% level of accuracy. The methodology used not only provides a classification of the hospitalized population, but also specifies the certainty with which each individual is classified correctly. The combined effort of the expertise of health care professionals in the subjectively defined medical services classification and clustering, and the power inherent in the statistical methodology used to empirically differentiate patterns, has yielded a mathematical model which approximates a complex decision process.

VI.1 Implications

The endeavor undertaken in this research has been basically methodological in nature. Had the resolution of the hypotheses posited been negative, some of the following issues would not be addressed. However, this not being the case, the costs and benefits of each model need to be evaluated.

A cost effectiveness analysis of continued stay reviews was performed by Averill and McMahon.² Their results indicate that the costs associated with continued stay reviews are not likely to be compensated for by the potential financial savings. They state that the potential savings may be increased if the feedback and corrective action are more

TABLE 6.1 Optimal Discriminating Variables for Inappropriate Utilization

Order Selected	Variable Number	Variable Name	Utility
1	X ₇	Medications (Intensity 1, Intensity 3)	High
2	X ₂₇	Hospital Based Service	
3	X ₃	Nursing (Intensity 5)	High
4	X ₁	Nursing (Intensity 1, Intensity 3)	High
5	X ₁₁	Medications (Intensity 3 IM & PO) (Intensity 5)	High
6	X ₁₇	Ancillary Diagnostic (Intensity 7)	High
7	X ₁₉	Ancillary Diagnostic (Intensity 9)	High

timely, that is decreasing the time for corrective action from 48 to 24 hours. They also state that if the selection method chooses a higher proportion of patients who are inappropriately located, then the financial benefits would increase. However, they felt that if the selection process were more complex, it would be more costly, which would in turn affect the potential financial benefits.²

Their findings and assertions indicate the importance of timely and accurate patient selection. Other studies support these assertions demonstrating that misutilized days can be decreased by efficacious feedback procedures.³

The proposed level of care index is timely because it reviews every patient each day and it has a significantly higher probability of identifying the patients who are inappropriately located.

To evaluate the relative cost effectiveness of the proposed level of care index and the PSRO length of stay selector model, the following factors need to be addressed.

The costs should include:

- 1) development and implementation of computer system of models, i.e., programming costs for coding all the medical services, for converting a patient's medical services profile into a service code cluster pattern, for the discriminant function evaluation, for creating a data base of computer recognizable diagnoses and automated assignment of lengths of stay, operating and maintenance costs of each model, etc.

- 2) cost of unnecessary review
 - a) when the URNC can use only MIS for arriving at a confident decision
 - b) when the URNC must use the chart to establish appropriate location.
- 3) cost of missing a misutilized day
 - a) when corrective action could have been initiated
 - b) for documentation purposes only.

The benefits should include:

- 1) proportion of coordinator's time spent reviewing patients with a higher probability of possible corrective action
- 2) effect on likelihood of loss of delegated status
- 3) effect on coordinator's decision making depending on criterion used for patient selection
- 4) effect on the effectiveness of Utilization Review when
 - a) providing feedback triggered by a process consistent with physician decision making if the physician had complete information on resources available for patient care, or
 - b) when triggered by other criteria.
- 5) accuracy of data on appropriate utilization of acute hospital and reasons for inappropriate utilization due to availability of alternative facilities.

It was not proposed that these questions would be answered here; it is strongly being suggested that this work be done.

VI.2 Conclusions

An effective and efficient utilization review system is of concern to various individuals and groups involved in the delivery of health care. Obviously, if it is not effective, it is not fulfilling its objective; if it is not efficient, it may not be justifying its *raison d'être*.

Utilization Review is primarily a classification problem--that of classifying patients into the appropriate health care institution according to their medical care needs. Although peer review is delegated to physicians, a physician representative can determine or screen patients for physician review. The use of Utilization Review Coordinators is one way of using physician time more efficiently, as well as increasing the likelihood that the review process is more effective.³ Length of stay by diagnosis has been proposed by the PSROs as the indicator to be used for deciding when to review a patient. A computerized decision model has been developed that can approximate the Utilization Review Coordinator's judgments. It is an index of the level of care required by a patient. The level of care index is a better indicator for determining which patients should be reviewed for probable misutilization.

NOTES

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2. Averill, R.F. and McMahon, L.F. "A Cost Benefit Analysis of Continued Stay Certification." *Medical Care*, 15:158, February 1977.
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APPENDIX A

DICTIONARY OF A SAMPLE OF
MEDICAL SERVICES AND ASSOCIATED CODES

The medical services were printed with the permission of the
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I would like to thank the Technicon MIS Corporation for their
cooperative assistance.

CLINICAL PATHOLOGY DEPARTMENT	
CODE	MEDICAL SERVICE
0102	L/S Ratio
0102	L/S Shake Test
3102	Frozen Section
3142	Blood Culture, One Arm, NOW - Frequency > BID
3142	IV Intra Cath Culture and IVP Tip - Frequency > BID
5142	Bleeding Time - Frequency > BID
5142	Blood Culture, One Arm, NOW - Frequency ≤ BID
5142	BSP, Dye Injected at <u> H </u> <u> M </u>
5142	Clotting Time - Frequency > BID
5142	Clotting Time - Lee-White - Frequency > BID
5142	IV Intra Cath Culture and IVP Tip - Frequency < BID
5142	Lee White - Frequency > BID
5142	Plasma Clot Time - Frequency > BID
5142	Pro Time - Frequency > BID
5142	Immu Diffus-CSF - Frequency > BID
5142	Tolbutamide Test, Injected at <u> H </u> <u> M </u>
5142	CSF Culture - Frequency > BID
5142	Blood Culture - Frequency > BID
5142	3 - Enzymes - Frequency > BID
5142	ABO Only - Frequency > BID
5142	Blood Amylase - Frequency > BID
5142	Urine Amylase - Frequency > BID
7102	Birth Products Exam

CLINICAL PATHOLOGY DEPARTMENT (continued)

CODE	MEDICAL SERVICE
7142	Bleeding Time - Frequency < BID
7142	Clotting Time - Frequency < BID
7142	Lee White - Frequency < BID
7142	Plasma Clot Time - Frequency < BID
7142	Pro Time - Frequency < BID
7142	Immu Diffus-CSF - Frequency < BID
7142	CSF Culture - Frequency < BID
7142	Blood Culture - Frequency < BID
7142	Blood Amylase - Frequency < BID
7142	Urine Amylase - Frequency < BID
7142	Blood Typing - RH Only
7142	Coagulation Time - Frequency < BID
7142	Crossmatch _____ Units
9142	Alcohol - Blood
9142	Alcohol - Urine
9142	Acetone - Blood
9142	Acetone - Urine
9142	Amino Acid - Quality
9142	Amino Acid - Quantity
9142	Blood Count
9142	Blood Glucose
9142	Chromosome Analysis
9142	Culture, Post-Cath
9142	Glucose Tolerance - 1 HR - PC
9142	Hemoglobin and PCV
9142	24 HR Urine Phosphorous
9142	Routine Urinalysis

CLINICAL PATHOLOGY DEPARTMENT (continued)

CODE	MEDICAL SERVICE
9142 9142 9142 9142 9142 9142	SMA - 18 Strep Culture Uric Acid - Blood Uric Acid- Urine VORL WBC

RADIOLOGY DEPARTMENT

CODE	MEDICAL SERVICE
0202	Abdominal Aortogram
0202	Air Study - Retroperitoneal
0202	Angiocardiography
0202	Aorto-Femoral Study
0202	Aortography
0202	Arch Aortogram
0202	Arterio-Veno Shunt Study
0202	Biopsy Study.
0202	Cardiac Catheterization
0202	Carotid Arteriogram - Bilateral
0202	Carotid Arteriogram - Right
0202	Carotid Arteriogram - Left
0202	Cholangiogram - Operating Room
0202	CO2 Injection
0202	Coronary Arteriogram and Left Ventriculogram
0202	Coronary Angiography
0202	Cyst Puncture - Renal
0202	Discogram
0202	Inferior Venacavagram
0202	Kidney Biopsy
0202	Peripheral Arteriogram - RIL
0202	Pneumoencephalography
0202	Pneumopericardium Study
0202	Pulmonary Arteriogram
0202	Pyelogram via Nephrostomy
0202	Myelography
0202	Renal Biopsy
0202	Retroperitoneal Air Study -

RADIOLOGY DEPARTMENT (continued)		
CODE	MEDICAL SERVICE	
0202	Retrograde Brachial Arteriography	
0202	Room for Cardiac Catheterization	
0202	Selective Abdominal Arteriography	
0202	Splenoportography	
0202	Superior Venacavagram	
0202	Temporary Pacemaker	
0202	Thoracic Aortogram	
0202	Ventriculography	
0202	Venacavography	
0202	Vertebral Arteriogram	
0242	X-Ray in Operating Room	
0242	Cardioversion	
0242	CSF Flow Study	
0242	Percutaneous Cordotomy	
0242	Portable Chest X-Ray (CCU Admit)	
0242	Radium Insert Study	
0242	Renal Vein Assay	
0242	Thermo Coagulation, _____	
1242	Pyelogram, Retrograde	
3202	Arthrography, _____	
3202	Bronchial Brushing	
3202	Bronchogram, Bilateral	
3202	Bronchogram, Unilateral	
3202	Hip Injection	
3202	Hysterosalpingogram	

RADIOLOGY DEPARTMENT (continued)

CODE	MEDICAL SERVICE
3202	Knee Arthrogram
3202	Laryngogram
3202	Lymphangiogram
3202	Parotid Gland
3202	Pelvic Pneumogram
3202	Peripheral Arteriography
3202	Peripheral Venography
3202	Pneumogram - Pelvic
3202	Shoulder Arthrogram
3202	Shunt Venogram
3202	Sialography
3202	Sinus Tract Injection
3202	Sublingual Gland
3202	Submandibular Gland
3202	Urethrogram - Retrograde
3202	Venography - Bilateral
3202	Venography - Peripheral
3202	Venography - Unilateral
3203	Biliary Stone Removal
3203	Radiation Therapy
5202	Cannula Venogram
5202	Cholangiogram - IV
5202	Cystogram
5202	Cystourethrogram - Voiding
5202	Dacryocystogram
5202	Esophageal Brushing

RADIOLOGY DEPARTMENT (continued)

CODE	MEDICAL SERVICE
5202	Hypertensive IVP
5202	Hypotonic Duodenography
5202	Infusion IVP
5202	IVP
5202	T-Tube Cholangiogram
5242	Dialysis Shunt Study
5242	Nephrotomogram
5242	Gallium Scan
7202	Air Contrast and Barium Enema
7202	BA Swallow - Esophagus
7202	Barium Enema
7202	Cardiac Fluoroscopy
7202	Esophagus
7202	Fluoroscopy of
7202	Small Bowel Series
7202	Upper Gastrointestinal Series
7202	Upper GI and Small Bowel
7202	Upper GI and Small Bowel Follow Through
7202	Upper GI Series (Prep N° 1)
7242	Baker Jejunostomy Catheter
7242	Bard Sump Drain (Shirley)
7242	Bile Bag
7242	Blood Volume CR-51
7242	Blood Volume - Double Label
7242	Blood Volume (Rise I-125)

RADIOLOGY DEPARTMENT (continued)

CODE	MEDICAL SERVICE
7242	Bone Scan
7242	Chest with Barium
7242	Coude Foley Catheter (Bardex-Tiemann)
7242	Coude Plain Catheter (Bardex-Tiemann)
7242	Drainage Bag
7242	Drainage Tube-K54
7242	Drainage Tube-K57
7242	Drainage Tube-K58
7242	Duodenal Drainage
7242	Filiform Catheter
7242	Foam Rubber
7242	Foam Strips (Foamex)
7242	Foley Catheter
7242	Free Thyroxin
7242	French Catheter
7242	GI Blood Loss
7242	Heart Scan
7242	I-131 Thyroid Uptake Only
7242	I-131 Thyroid Uptake and Scan
7242	Kidney Scan
7242	Leg Drainage Bag (Dispoza)
7242	Liver Scan - Rose Bengal
7242	Liver Scan - Routine
7242	Liver/Lung Scan
7242	Lumbosacral Spine (Bending)
7242	Lung Scan
7242	Lung Scan (Ventilation)
7242	Moleskin Strips

RADIOLOGY DEPARTMENT (continued)

CODE	MEDICAL SERVICE
7242	Nuclear Medicine Visit
7242	Penrose Drain
7242	Placental Localization
7242	Brain Scan
7242	Schilling Test - Part A
7242	Schilling Test - Part B
7242	Schilling Test
7242	RBC Survival and Spleen/Liver Ratio
7242	RBC Survival CR-51
7242	Renal Scan
7242	Renogram
7242	Robinson Catheter
7242	Thyroid Scan Only
7242	T-3 Assay
7242	T-3 Suppression Test
7242	T-3/T-4 (Free Thyroxin)
7242	T-3
7242	T-4 Assay (Murphy-Pattee)
7242	T-4
7242	Trocath Dialysis - Stylet and Conect Tube
7242	TSH Stimulation Test
7242	URI-Meter Catheter
7242	URO-Sheath Catheter
7242	Portable X-Rays with a 7 Intensity Modality
9202	Read Outside Films
9242	Portable X-Rays with a 9 Intensity Modality

RADIOLOGY DEPARTMENT (continued)

CODE	MEDICAL SERVICE
9242	3-Way Abdomen
9242	Abdomen
9242	Abdomen - AP Only
9242	Abdomen - AP View
9242	Abdomen, AP/Lateral (Aneurysm)
9242	Abdomen, AP/Lateral (Umbilical Cath Position)
9242	Abdomen, IUD Localization
9242	Abdomen, General Survey, B-Mode
9242	Abdomen, Limited Survey Study, B-Mode
9242	Acromioclavicular Joint(s)
9242	Admission Chest
9242	Ankle
9242	Aorta, B-Mode
9242	Auditory Canal
9242	Bending Lumbar Study
9242	Bone Age - Hand and Wrist
9242	Bone Age - PA Hand and Wrist
9242	Bone Survey
9242	Bone Survey including Long Bones
9242	Cardiac Cinefluoroscopy
9242	Cardiac Series
9242	Cervical Neck for Soft Tissues
9242	Cervical Spine
9242	Cervical Spine-Lateral Only
9242	Chest - PA and Lateral
9242	Chest - PA
9242	Chest X-Ray
9242	Chest - Oblique

RADIOLOGY DEPARTMENT (continued)	
CODE	MEDICAL SERVICE
9242	Chest - Lateral
9242	Chest - Lateral Decubitus
9242	Chest - Inspiring and Expire
9242	Chest - AP, Portable Erect
9242	Chest - AP, Portable Supine
9242	Chest - Apical Lordot
9242	Chest - PA and Right Lateral
9242	Chest - PA and Left Lateral
9242	Cholecystogram - Loading Technique
9242	Cholecystogram - Repeat Dose
9242	Cholecystogram
9242	Clavicle
9242	Coccyx and Sacrum
9242	Colon
9242	Comparison Exam _____
9242	Dorsal Spine
9242	Dorsolumbar Spine
9242	Echocardiogram, Complete, M-Mode
9242	Echocardiogram, Follow-up, M-Mode
9242	Elbow
9242	Entire Spine
9242	EST Study
9242	Eye for Foreign Body
9242	Facial Bones
9242	Femur
9242	Fingers, Both Hands
9242	Fingers, Left Hand
9242	Fingers, Right Hand

RADIOLOGY DEPARTMENT (continued)	
CODE	MEDICAL SERVICE
9242	Foot
9242	Foot - Toes
9242	Forearm
9242	Gallbladder
9242	Gallbladder Sonogram, B-Mode
9242	Gallbladder - Loading Technique
9242	Gallbladder - Repeat
9242	Hand
9242	Heel(s)
9242	Hip - AP and Lateral
9242	Humerus
9242	Intrauterine Device Localization, B-Mode
9242	Kidney Sonogram, B-Mode
9242	Knee
9242	KUB
9242	Kymography Study
9242	Liver Sonogram, B-Mode
9242	Long Bone Survey
9242	Lower Leg
9242	Lumbosacral Spine
9242	Lumbosacral Spine (Bending)
9242	Mammogram
9242	Mandible
9242	Mastoid
9242	Maxilla
9242	Midline Determination, A-Mode
9242	Motor Meal Study
9242	Nasopharynx

RADIOLOGY DEPARTMENT (continued)

CODE	MEDICAL SERVICE
9242	Nasal Bone
9242	Neck
9242	Neck, PA and Lateral
9242	Optic Foramina
9242	Orbit
9242	Pancreas Sonogram, B-Mode
9242	Patella
9242	Pelvis
9242	Pelvimetry
9242	Pelvic Mass Sonogram, B-Mode
9242	Pericardial Effusion, M-Mode
9242	Petrous Bone
9242	Placenta Localization, B-Mode
9242	Pleural Effusion Localization, A-Mode
9242	Post Reduction
9242	Pre-Op Chest
9242	Pregnancy and Fetal Age Determination, B-Mode
9242	Repeat Fetal Age Determination, B-Mode
9242	Retroperitoneal Space Sonogram, B-Mode
9242	Ribs
9242	Ribs, Bilateral
9242	Ribs, Unilateral
9242	Sacroiliac Joint
9242	Sacrum and Coccyx
9242	Scapula
9242	Scanogram
9242	Sella Turcica
9242	Shoulder

RADIOLOGY DEPARTMENT (continued)

CODE	MEDICAL SERVICE
9242	Sinuses - Routine
9242	Sinus Series
9242	Skeletal Survey
9242	Skull - Trauma Routine
9242	Skull - PA
9242	Skull - Neuro Routine
9242	Skull
9242	Soft Tissues - Cervical Neck
9242	Spine - Cervical
9242	Spine - Dorsolumbar
9242	Spine - Lumbosacral
9242	Spine - Thoracic
9242	Spine - Dorsal
9242	Spine - Lumbar
9242	Spleen Sonogram, B-Mode
9242	Sternoclavicular Joint(s)
9242	Sternum
9242	Teeth
9242	Thigh
9242	Thoracic Spine
9242	Thyroid Sonogram, B-Mode
9242	T-M Joint
9242	Toes (Right Foot or Left Foot or Both Feet)
9242	Tomogram
9242	Ultrasonic Guidance for Biopsy/Aspiration
9242	Urinary Bladder Sonogram, B-Mode
9242	Wrist
9242	Xeromammography

RADIOLOGY DEPARTMENT (continued)		
CODE	MEDICAL SERVICE	
9242	Xeroradiography of _____ X-Ray for Umbilical Catheter X-Ray, Chest Zygomatic Arch	
9242		
9242		
9242		

NURSING DEPARTMENT	
CODE	MEDICAL SERVICE
0311	Attach External Transducer
0311	Attach Internal Fetal Electrode
0311	Attach Labor Transducer
0311	Blood Pressure and Pulse Stat, Then Q15M for 2 Hours, Then Q30M for 2 Hours, Cardiac Monitor Unit
0311	Check Right Groin for Signs of Bleeding, Q15M for 2 Hours, Then Q30M for 4 Hours.
0311	Check Right Foot Pulse at Time of Right Groin Check.
0311	Check Left Groin for Signs of Bleeding, Q15M for 2 Hours, Then Q30M for 4 Hours.
0311	Check Left Foot Pulse at Time of Left Groin Check.
0311	EKG Monitoring
0311	Nurse: Have Arterial Blood Gases Taken 1 Hour After Starting Ventilation
0313	Connect Chest Tube
0313	Rotating Tourniquet, PRN Emergency
0313	Umbilical Catheter - Art/Ven With
0317	If Patient Does Not Void, Repeat Load and Notify Doctor
0317	Intravenous Medications - Volutrols with Medication Additive - Special List
0319	Admit to Labor Room
0320	Semi OB Prep On Admit
0321	Reinforce Soiled Dressings PRN. If Excessive Bleeding Call Doctor
0321	Reinforce Soiled Dressings PRN (Post Angiogram and Catheterization)
0325	Bucks Traction
0325	Steinman Traction: Continuous Traction with Pinning

NURSING DEPARTMENT (continued)	
CODE	MEDICAL SERVICE
0327	Advance All Pre-Op Medications
0327	IM Medications - Special List
1311	Blood Pressure, Pulse, Respiration - Q2H, Omit when Asleep if Condition Stable
1311	Nurse: Notify MD of all Blood Gas Results and Respirator Changes
1311	Vital Signs - Greater than 6 Times Per Day (Includes Q1H 'Til Stable)
1311	Vital Signs - Q5M for 2 Hours, Then Q4H first day Post Anesthesia
1311	Neuro Signs - Q1H or Q2H
1311	Vital Signs - Pulse, Respiration, Check Circulation Q1H
1311	Vital Signs - Q1H Blood Pressure and Machine Check in AKU
1311	Vital Signs - Q2-20M 'Til Stable, Then Q2H Times 4.
1311	Vital Signs - Routine Post Op for 24 Hours, Includes All Orders
1311	Order Blood Sugar PRN for Signs of Insulin Reaction
1311	Obtain Cardiac Monitoring Unit
1313	Leave Endotracheal Tube in Place and Ventilate as per Standard Order
1313	Dialysis Frequency _____ Times/Week
1313	Dialysate _____
1313	Heparinize, Init Dose _____ U in AKU
1313	Hours of Dialysis _____
1313	AKU Nurse _____
1313	Anticoagulation (AKU)
1313	Begin Dialysis (AKU)
1313	Bed Scale (AKU)
1313	Bedside Monitor (AKU)
1313	Duration (AKU)
1313	Medications (AKU)
1313	Nurse: Give Following Instructions to Patient (AKU)

NURSING DEPARTMENT (continued)	
CODE	MEDICAL SERVICE
0327	Advance All Pre-Op Medications
0327	IM Medications - Special List
1311	Blood Pressure, Pulse, Respiration - Q2H, Omit when Asleep if Condition Stable
1311	Nurse: Notify MD of all Blood Gas Results and Respirator Changes
1311	Vital Signs - Greater than 6 Times Per Day (includes Q1H, T11 Stable)
1311	Vital Signs - Q5M for 2 Hours, Then Q4H first day Post Anesthesia
1311	Neuro Signs - Q1H or Q2H
1311	Vital Signs - Pulse, Respiration, Check Circulation Q1H
1311	Vital Signs - Q1H Blood Pressure and Machine Check in AKU
1311	Vital Signs - Q2-20M T11 Stable, Then Q2H Times 4.
1311	Vital Signs - Routine Post Op for 24 Hours, Includes All Orders
1311	Order Blood Sugar PRN for Signs of Insulin Reaction
1311	Obtain Cardiac Monitoring Unit
1313	Leave Endotracheal Tube in Place and Ventilate as per Standard Order
1313	Dialysis Frequency _____ Times/Week
1313	Dialysate _____
1313	Heparinize, Init Dose _____ U in AKU
1313	Hours of Dialysis _____
1313	AKU Nurse _____
1313	Anticoagulation (AKU)
1313	Begin Dialysis (AKU)
1313	Bed Scale (AKU)
1313	Bedside Monitor (AKU)
1313	Duration (AKU)
1313	Medications (AKU)
1313	Nurse: Give Following Instructions to Patient (AKU)

NURSING DEPARTMENT (continued)	
CODE	MEDICAL SERVICE
1313	Post Dialysis Weight
1313	Unit Tests (AKU)
1313	Volume Replacement (AKU)
1317	Albumin (12.5 grams)
1317	Fibrinogen
1317	Cryoprecipitate (Factor VIII)
1317	Fresh Frozen Plasma
1317	IV Push
1317	IV - Volutrols with Medication Additive
1317	IV - Volutrols with Medication Additive - Special List
1317	IV - Narcotic Medications - Volutrols or IV Push
1317	IV - Volutrols - Special List: Heparin, Insulin, Hydrocortisone
1317	Packed Red Cells
1317	Platelets
1317	Insert Heparin Plug
1317	Whole Blood
1317	Cryoprecipitates
1326	Articles Must Be Discarded or Double Bagged and Sent to Central Supply
1326	Suicide Precautions
1326	Gowns Must Be Worn
1326	Hands Must Be Washed on Entering and Leaving Room
1326	Isolation Food Tray
1326	Masks Must Be Worn
1326	Articles Contaminated by Secretions Must Be Double Bagged
1326	Complete Isolation

NURSING DEPARTMENT (continued)	
CODE	MEDICAL SERVICE
1327	IM Medications - Special List
1327	PO Medications - Special List
3311	Neuro Check - Pupils, Grasp, Orientation
3311	Neuro Check - Pupils
3311	Neuro Check - Response
3311	Neuro Check - Weakness
3311	Vital Signs Q15M for 2 Hours, Then Q4H AFTER First Day Post-Op
3313	Insert <u>Tube</u> (NG, Endotracheal)
3313	Irrigate - IV Catheter
3313	Insert Kantor Tube
3317	Clysis Medications - with Additive
3317	IV Fluids - Continuous or Daily (KCL, Vitamins, etc)
3317	AMF - 250 or 500 or 1000 Units
3317	To 5% D/Lac Ringers, 1000 CC When Patient Alert and If In Pain Add _____
3321	Routine Vital Signs First Post-Op Day/24-48 Hours Post-Op
3321	Vital Signs 5 to 6 Times per Day or Q4H
3323	Begin Coronary Rehabilitation
3323	Cord Clamp Off P 12 Hours When Cord is Dry. Alcohol Applied TID
3323	Encourage 10 Deep Breaths Q1H by Day (Q4H At Night) While on Narcotics
3323	Turn, Cough, Deep Breathe - Q1H
3326	Escape Precautions
3326	Seizure Precautions
3326	DT Precautions

NURSING DEPARTMENT (continued)	
CODE	MEDICAL SERVICE
3326	Radiation Precaution
3327	IM Medications At Least QID Except Narcotics, Post-Op, Special List
3327	IM Medications - Narcotics and Hypnotics
3327	IM Medications - Post-OP (Routine Non-Narcotic, Phenergen, Vistaril, Thorazine for Nausea)
3327	PO Medications - Special List
5311	Nurse: Notify MD of Any Persistent
5311	Nurse: Notify MD of Any Persistent (Rectal Bleeding, Excessive Bleeding)
5311	Nurse: Notify MD of <u>4</u> Times Each Day (S and A Results, Chest Pain, Bleeding)
5312	Gastric Analysis
5313	Aspirate Stomach and Lavage PRN Mucus
5317	Clysis Medications - Continuous or Daily
5319	Diabetic Teaching; Pre-Op Teaching: Colostomy, Ileostomy
5321	Nursing Observation: Check Circulation, Check Wound, Etc. Unstable Condition
5321	Record Amount Q Voiding
5321	Record Input and Output
5321	Record Input and Output - Fluid Restriction
5321	Record Input and Output - Q4H
5321	Record Separate Inputs
5321	Record Separate Inputs - Catheterize After Voiding - Measure Residual
5321	Record Separate Outputs
5321	Record Separate Outputs - Catheterize After Voiding - Measure Residual
5321	Frequent Nursing Observation: Check Casts and Extremities for Ortho and Vascular Surgery

NURSING DEPARTMENT (continued)	
CODE	MEDICAL SERVICE
5321	Record Time and Amount
5321	Record Time and Amount - Catheterize After Voiding - Measure Residual
5321	Record All Food Eaten and Amount in Nurse's Notes
5322	Sugar and Acetone - Q4H Unit Clinitest
5322	Specific Gravity and Volume Q2H - Unit Clinitest
5323	Catheterize PRN. If 2nd Cath Needed, Call MD; French Cath
5323	Hypothermal Blanket and/or Tepid Sponge PRN Temp Spiking
5323	Encourage Frequent Limb Exercises and Position Changes. Range of Motion by Nurse
5323	Encourage Leg Exercises, Q2H While Awake or 5 Times Per Day
5323	Flat On Back 2-4 Hours, Then Logroll Q1-2H
5323	Post Biopsy: Lie on Right Side 4 Hours, Then 6-8 Hours Bedrest for 24 Hours
5323	Foley Catheter N° 16 If Unable to Void
5323	Foley Catheter to Straight Drainage
5323	Harris Flush PRN Abdominal Distention
5323	Instruct to Cough and Deepbreathe Q2H
5323	Irrigate _____ Tube (NG), Irrigate Colostomy
5323	Lavage _____
5323	Tube Feedings Per NG/ NG To Intermittent Suction/
5323	Suction - Endotracheal
5323	Hemovac Instructions - Keep Compressed - Record Amount
5323	Turn, Cough, Deepbreathe - Q2H
5323	Turn Side to Side Q2H - Keep Off Back As Much As Possible; Turn Frequently
5323	Blow Bottles Q1H
5325	Traction - Intermittent/ At Night
5326	Restrict to Unit

NURSING DEPARTMENT (continued)	
CODE	MEDICAL SERVICE
5327	IM Medications - Less Frequent Than QID
5327	PO Medications - Special List
7310	Have RN Cut Toenails - Diabetic Patient
7312	Read Skin Test Ordered At
7312	Read Coccidioidin Test At 24 and 48 and 72 Hours
7312	Read Frei Test At 24 and 48 and 72 Hours
7312	Read HistoPlasmin Test At 24 and 48 and 72 Hours
7312	Read Mumps Test at 24 and 48 Hours
7312	Read PPD Test At 24 and 48 and 72 Hours
7312	Read Schick Test at 24 and 48 and 72 Hours
7312	Read TB Line Test at 48 and 72 Hours
7312	Read Toxoplasmin Test at 24 and 36 and 72 Hours
7320	Insert Rectal Tube PRN or For One Hour; Check for Impaction
7320	Measure Abdomen QD
7320	Weigh Patient Daily or QOD
7320	Routine Vital Signs; Vital Signs 1 - 4 Times Per Day
7321	Record Stool - Quality and Quantity; Check for Rectal Bleeding
7321	Record Suction Unit Vol-Empty-DC in 24H; Collect All Sputum for MD to See
7321	Strain Urine; Save All Urine; Measure Volume Daily
7322	Dextrostix
7322	Unit Clinitest; Unit Test - Guaiac Stool and Hematest Stools, Sugar And Acetone QID
7323	Oxygen 3L/Min. By Nasal Cannulae While On Narcotics; All Oxygen Orders

NURSING DEPARTMENT (continued)	
CODE	MEDICAL SERVICE
7323	Blow Bottles Q2H
7323	Clamp NG/Intestinal Tube, T-Tube, Clamp Excision 1 Hour After Meal
7323	Compress, Pack, Soak and Decubitous Care Q4H with Maalox
7323	Dressings; Wrapping Bandages; Check for Stump Bandages
7323	Ice Collars; Ice Packs; Ice Pack to Operative Area for 48 Hours
7323	Irrigate - Foley, French Catheter; All Catheter Care Routines, Including Suprapubic
7323	Remove NG/Intestinal Tube
7323	Remove Catheter and Tube
7323	Suction - Oral, Nasal, Pharynx; Jackson or Pratt Drain
7323	Supports and Binders: Anti-Embolism Stockings, Slings, Traction Corset, Cervical Collar
7323	Supports and Binders: Rib Binder, Heel Pads, Splint Between Legs, Ace Abdomen
7323	Turn, Cough, Deep Breathe and May Log Roll PRN Q4H, Encourage Coughing Q4H
7323	Remove Pressure Dressing in A.M.
7323	Remove Impaction
7325	Cervical Traction
7325	Lumbar Traction
7325	Patient to Use Traction 50% of Time
7325	Return to Traction in 24 Hours
7325	Traction Orders - e.g. Pelvic Traction May Release PRN
7326	Restraints or 4 Side Rails At All Times
7327	PO Medications - NG Medications, Oral Suspensions
7327	PO Medications - Narcotics
7327	PO Medications - Routine Non-Narcotics, Compazine, Aspirin, Pain, Fever, Laxative, Antacid
9320	Encourage Fluids; Force Fluids

NURSING DEPARTMENT (continued)	
CODE	MEDICAL SERVICE
9320	Abdominal-Peri Prep; Breast and Groin Shave; All Preps
9320	Enema, Saline, HS, Lo
9320	Thoracic Tray, Obtain Spec. Shoes, Eye Dressings Equipment at Bedside
9320	Heat Lamp; Shock Blocks, Bedside Stool, Bedboard, Weights for Arm, Sheepskin
9320	Heat Cradle; Heating Pad, Perillight, Trapeze, Walker
9320	Notify MD of Lab Results
9320	Sitz Bath PRN; Daily Shower; Sitz Bath BID to QID; Douche BID
9320	Phisohex Surgical Prep and Shave; Betadine Scrub X 2; Douche with Phisohex
9320	Enema include Fleets PRN and Soap Suds
9320	Soap Suds Enema on Admit
9320	Suprapubic Prep
9323	Bed Rest for 6HR with Left or Right Leg Raised
9323	Foley in But No Special Care; Suprapubic in Past 3rd Day
9323	Skin Care; Bathe Feet Q Day with Phisohex; Mouth Care
9323	Ambulate, Positioning Orders: Get up in W/C, Elevate Foot of Bed, Range of Motion BID
9323	Positioning Orders: Elevate Foot of Bed for 20 Degrees for 15 Min Q8H; Dangle Today
9323	Heat Lamp IID; K-Pad QID for 20-30 Minutes; Heating Pad X 3
9323	Blow Bottles

PHYSICAL AND OCCUPATIONAL THERAPY DEPARTMENT	
CODE	MEDICAL SERVICE
1443	Tilt Table
5443	Physical Therapy - Patient on Continuous Traction
7443	Physical Therapy - Intermittent Cervical Traction QD - BID
7443	Physical Therapy - Intermittent Pelvic Traction QD - BID
7443	Physical Therapy - BID
9443	Physical Therapy
9443	Physical Therapy at Patient Bedside
9443	Massage and Hot Pack to Neck - BID
9443	Occupational Therapy

RESPIRATORY MEDICINE	
CODE	MEDICAL SERVICE
0543	Controlled Ventilation - Volume Ventilation
0543	Mechanical Ventilation
0543	Controlled Ventilation - Pressure Ventilation
1502	Complete Exercise Evaluation
1542	Arterial Blood Gases QID
1543	Percussion Postural Drainage Q2H
1543	IPPB Q2H
3543	IPPB Q4H and Ultrasonic Nebulizer - Q3H with Additive
3543	Percussion Postural Drainage Q4H and Q3H While Awake
5502	Anatomic Shunt Evaluation (100° Oxygen)
5542	Arterial Blood Gases
5542	Pulmonary Medicine: Bedside Screening
5542	Pulmonary Function with <u>Isuprel</u>
5542	Pulmonary Function with Bronkosol
5542	Routine Pulmonary Function
5542	Spirometry Only
5542	Spirometry Only - Administer Nebulized
5542	Measure Arterial Blood Gases Preop on Room Air, Call Surgeon if Over 50MMHG
5542	Full Pulmonary Function Studies Before and After Bronchodilator
5543	Incentive Spirometer QID
5543	IPPB 15 MM HG Pressure for <u> </u> Min QID

RESPIRATORY MEDICINE (continued)	
CODE	MEDICAL SERVICE
5543	Gas Therapy
5543	IPPB Alternate USN
5543	IPPB With USN
5543	Nebulizer, Ultrasonic QID
5543	Percussion - Postural Drainage QID
5543	Ultrasonic Nebulizer for Sputum Induction
5549	Pre-Op Respiratory Teaching; Respiratory instructions for home use
7542	Diffusing Capacity
7543	Incentive Spirometer BID
7543	IPPB BID
7543	USN BID
7543	Nebulizer: BID, Overnight, When Trach not Plugged, PRN
7543	Nebulizer, Hand: For administration of Drugs BID, QID, Q4H

ATTENDING PHYSICIAN(S)	
CODE	MEDICAL SERVICE
0603 0603 0603	Surgery - Patient in or Scheduled for the Day Extubate Only When Fully Awake - Ventilates Until Then Hip Pinning
0607	Intrathecal Medications
0608	Kidney Biopsy
1608 1608	Liver Biopsy Tracheotomy
3608 3608	Thoracostomy Thoracentesis
5608 5608 5608 5608 5608	Aspiration Bone Biopsy, Muscle Biopsy, Testes Biopsy Colonoscopy and Rectal Biopsy Esophageal Dilatation Lumbar Puncture
7608 7608 7608 7608	Remove Supra Catheter Anoscopy Nasal Packing Sigmoidoscopy and Biopsy
9608 9608 9608	Pelvic Exam Suture Removal - Plastic Change Dressings

ELECTROCARDIOGRAM, ELECTROENCEPHALOGRAPH, ELECTROMYEOGRAM DEPARTMENTS	
CODE	MEDICAL SERVICE
5742	EKG - Double Masters
5742	EKG - Ergometer
5742	EKG - Masters
5742	EKG - Treadmill
7742	EEG
7742	EEG - With Photic Stimulation
7742	EKG - Rhythm Strip
7742	EKG - Standard
7742	Phonocardiogram
7742	EMG
7742	Vectorcardiogram

APPENDIX BUTILITY CURVES FOR SERVICE CODE CLUSTERS
AS A FUNCTION OF AGE AND PRN/non-PRN FACTORS

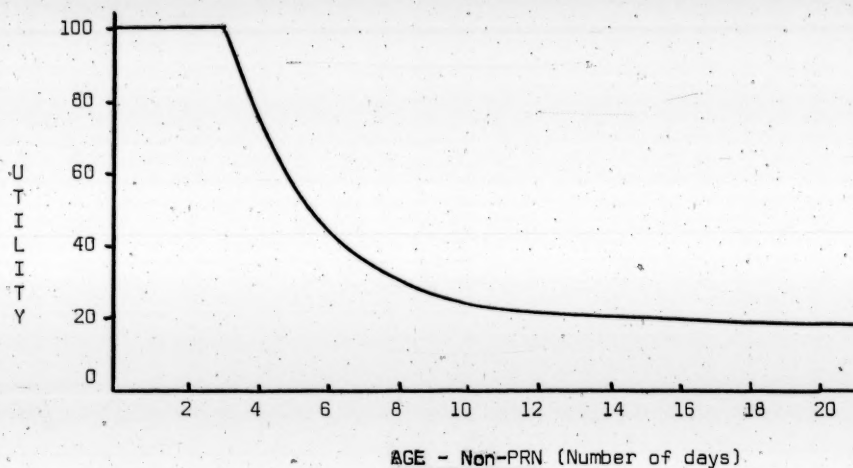


FIGURE 1.1a UTILITY CURVE FOR AGE - Non-PRN OF CLUSTER,
NURSING (Intensity 1, Intensity 3)

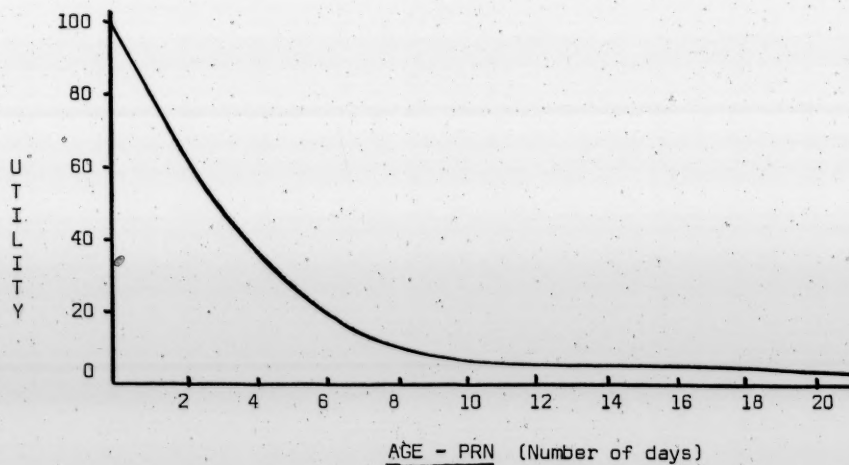


FIGURE 1.1a UTILITY CURVE FOR AGE - PRN OF CLUSTER
NURSING (Intensity 1, Intensity 3)

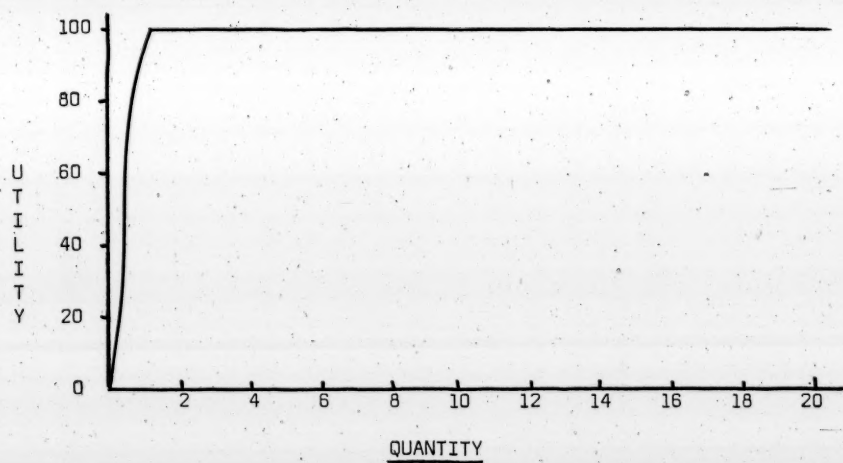


FIGURE 1.1q UTILITY CURVE FOR QUANTITY OF CLUSTER
NURSING (Intensity 1, Intensity 3)

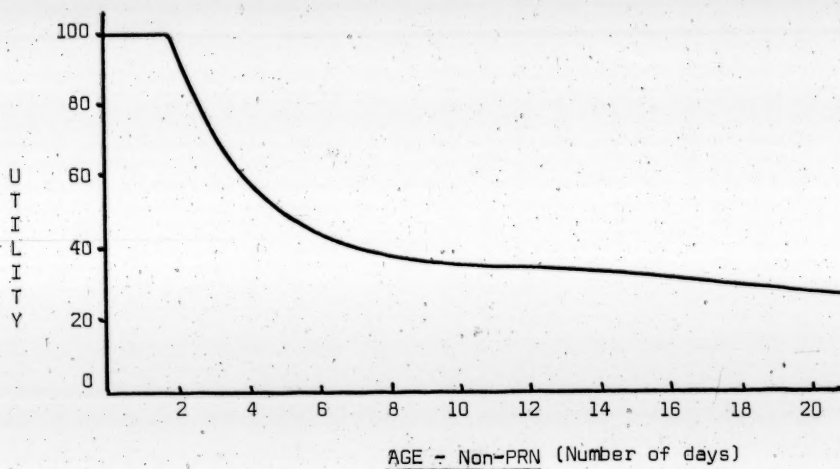


FIGURE 1.2a UTILITY CURVE FOR AGE - Non-PRN OF CLUSTER
NURSING (Intensity 5)

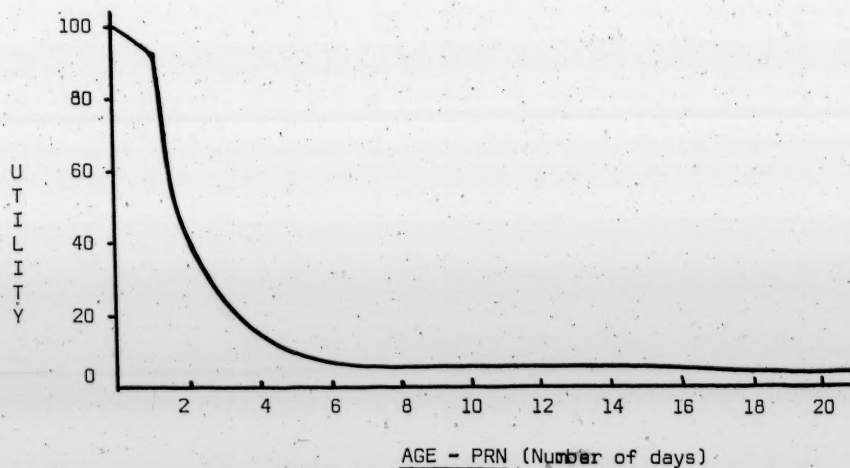


FIGURE 1.2a UTILITY CURVE FOR AGE - PRN OF CLUSTER
NURSING (Intensity 5)

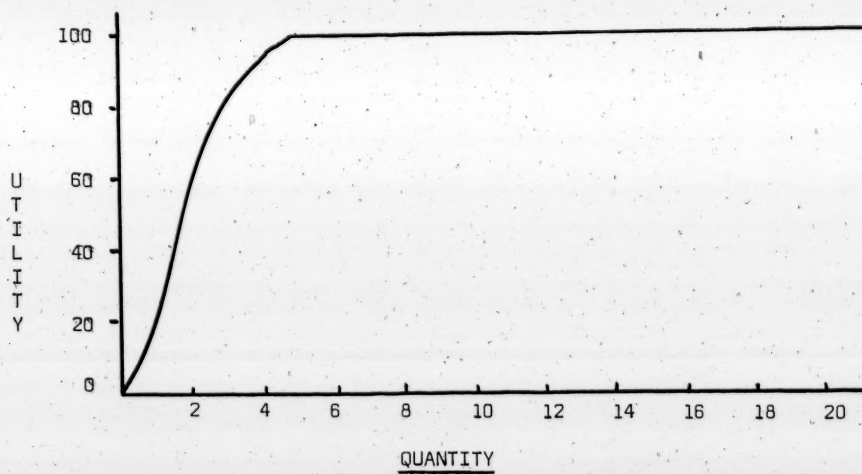


FIGURE 1.2q UTILITY CURVE FOR QUANTITY OF CLUSTER
NURSING (Intensity 5)

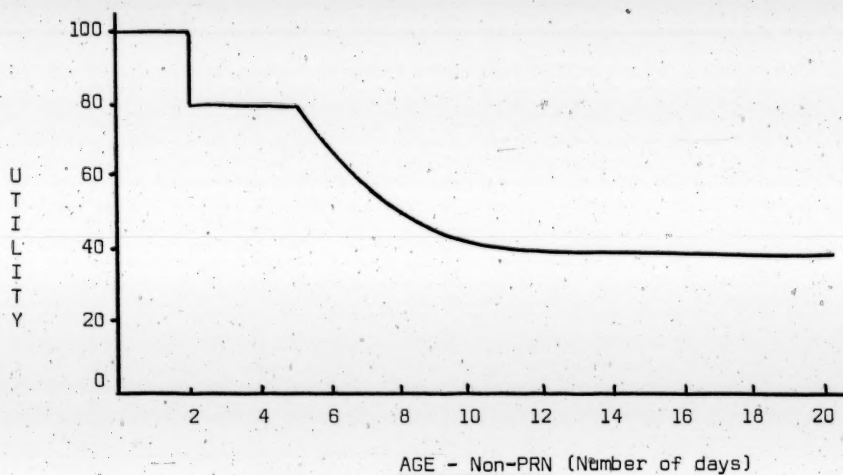


FIGURE 1.3a UTILITY CURVE FOR AGE - Non-PRN OF CLUSTER
NURSING (Intensity 7)

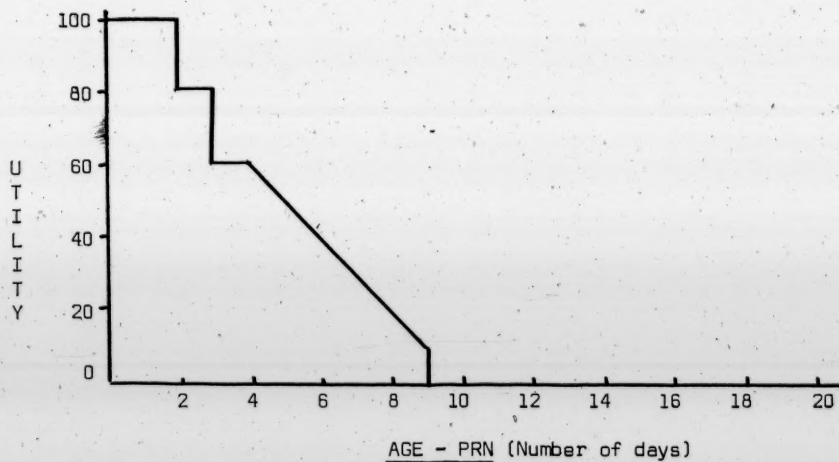


FIGURE 1.3a UTILITY CURVE FOR AGE - PRN OF CLUSTER
NURSING (Intensity 7)

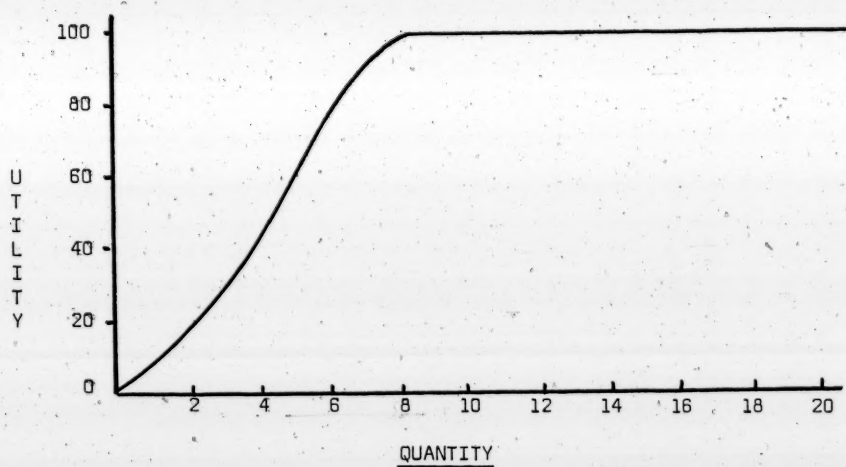


FIGURE 1.3q UTILITY CURVE FOR QUANTITY OF CLUSTER
NURSING (Intensity 7)

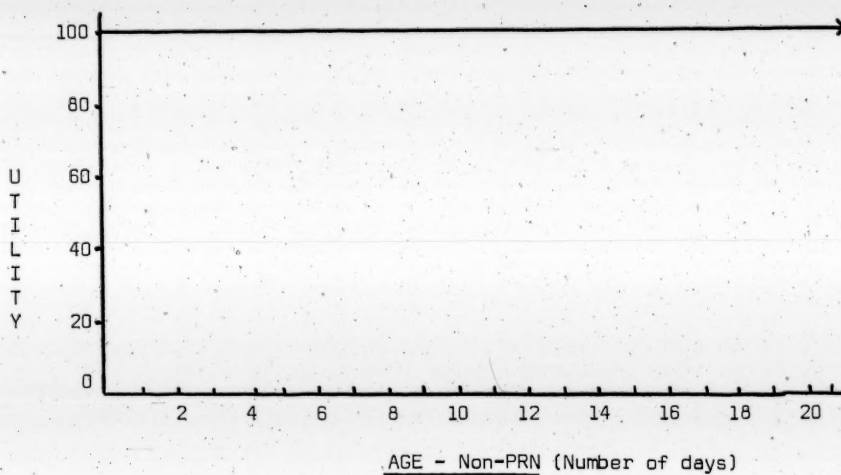


FIGURE 1.4a UTILITY CURVE FOR AGE - Non-PRN OF CLUSTER
MEDICATIONS (Intensity 1, IV Intensity 3)

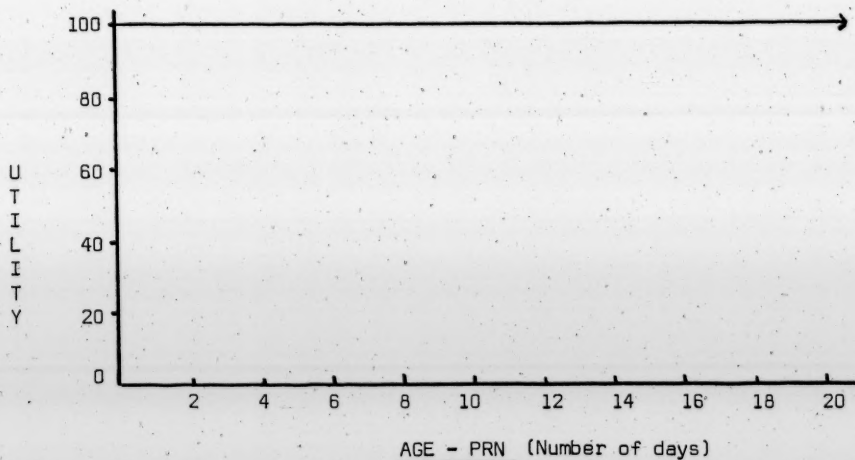


FIGURE 1.4a UTILITY CURVE FOR AGE - PRN OF CLUSTER
MEDICATIONS (Intensity 1, IV Intensity 3)

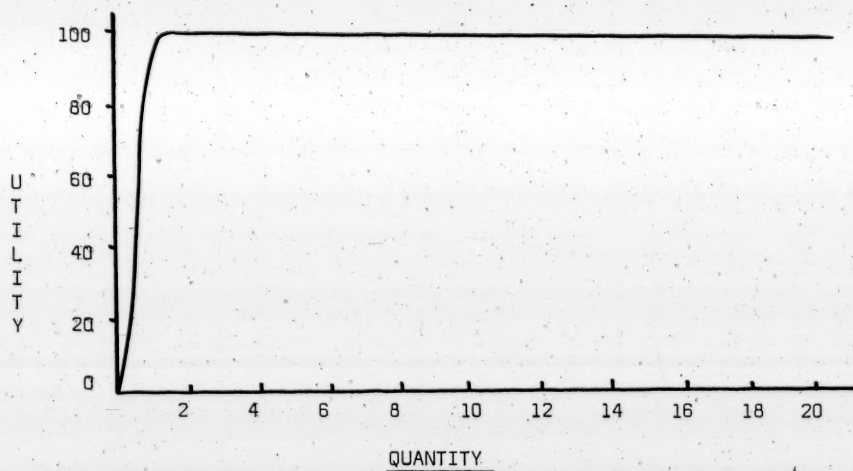


FIGURE 1.4q UTILITY CURVE FOR QUANTITY OF CLUSTER
MEDICATIONS (Intensity 1, IV Intensity 3)

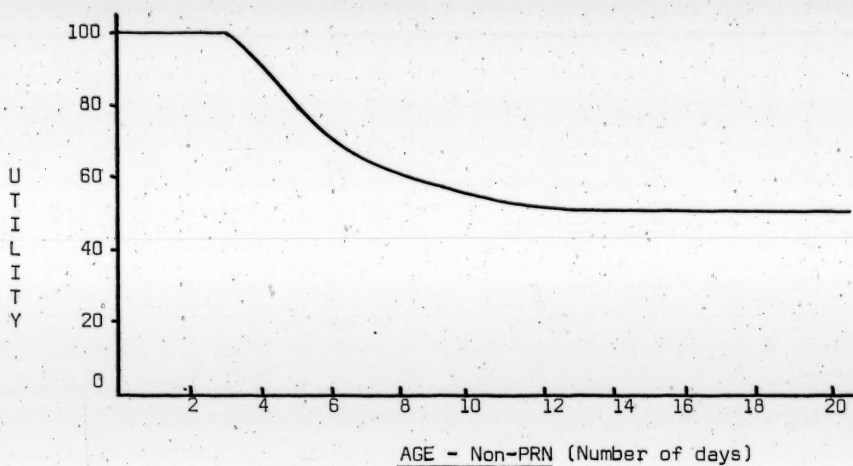


FIGURE 1.5a UTILITY CURVE FOR AGE - Non-PRN OF CLUSTER
MEDICATIONS (Intensity 3 IM & PO, Intensity 5) Non-PRN

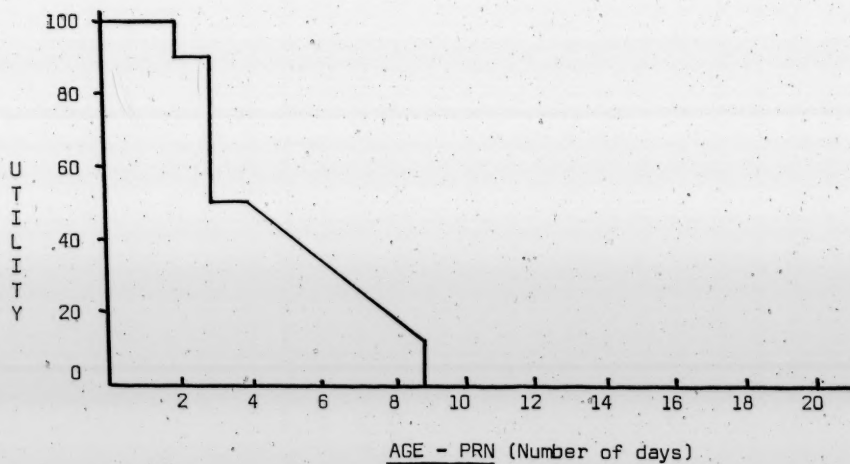


FIGURE 1.6a UTILITY CURVE FOR AGE - PRN OF CLUSTER
MEDICATIONS (Intensity 3 IM & PO, Intensity 5) PRN

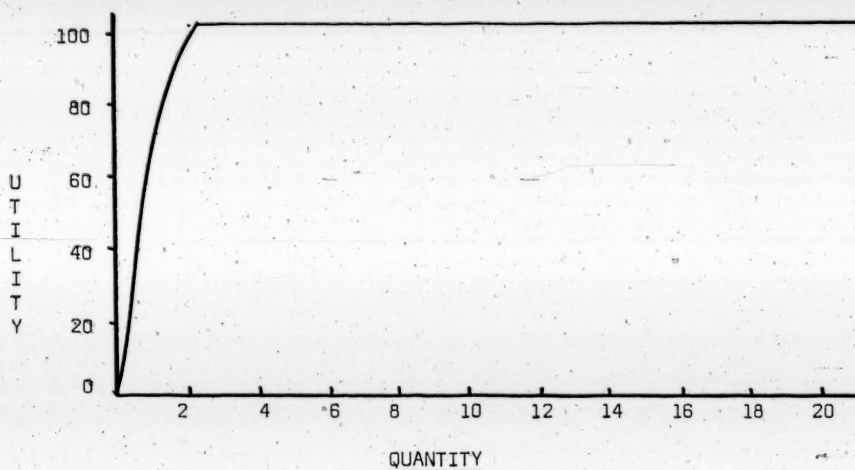


FIGURE 1.5q UTILITY CURVE FOR QUANTITY OF CLUSTER
MEDICATIONS (Intensity 3 IM & PO, Intensity 5) Non-PRN

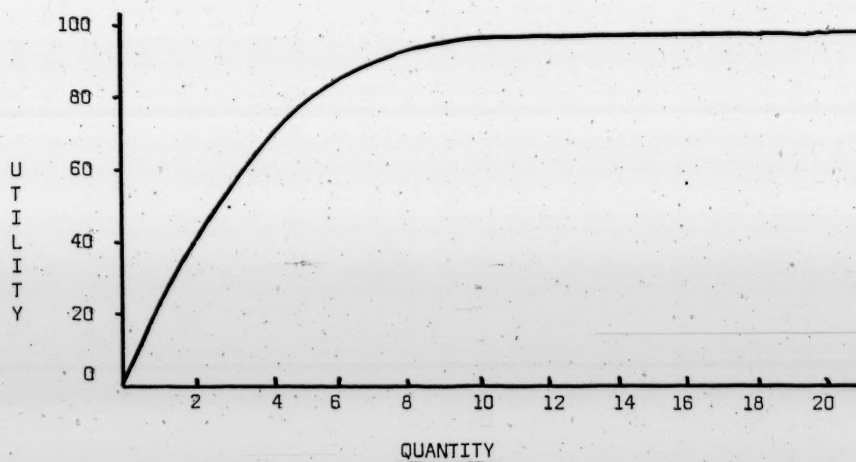


FIGURE 1.6q UTILITY CURVE FOR QUANTITY OF CLUSTER
MEDICATIONS (Intensity 3 IM & PO, Intensity 5) PRN

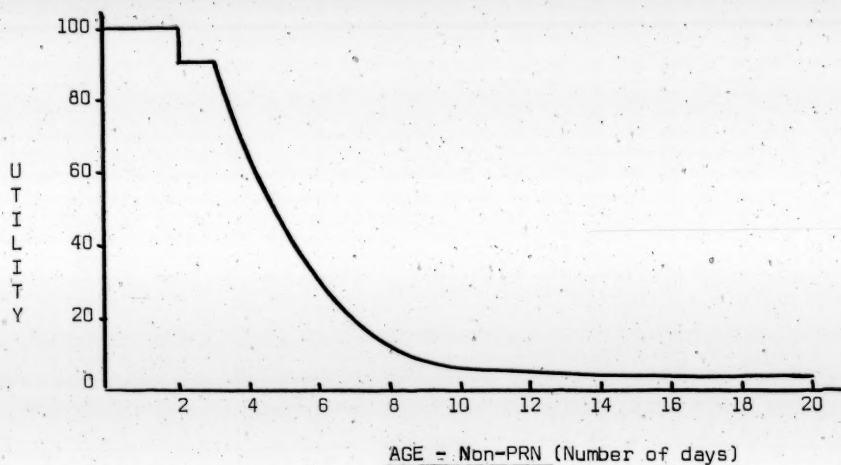


FIGURE 1.7a UTILITY CURVE FOR AGE - Non-PRN OF CLUSTER MEDICATIONS (Intensity 7)

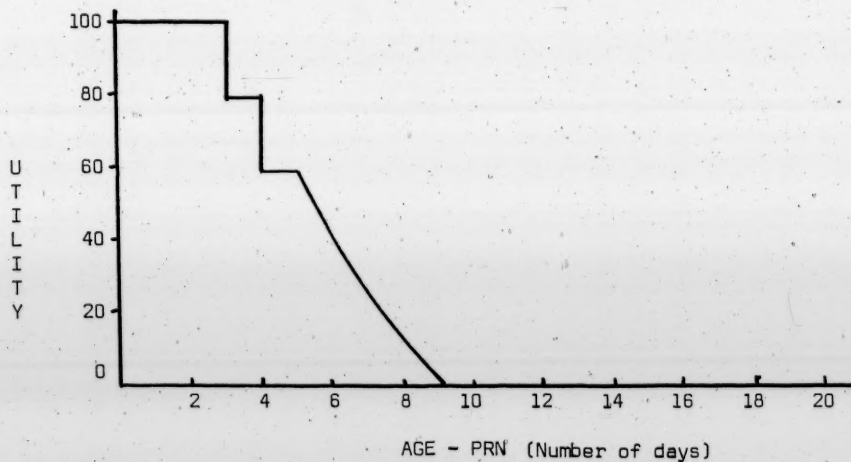


FIGURE 1.7a UTILITY CURVE FOR AGE - PRN OF CLUSTER MEDICATIONS (Intensity 7)

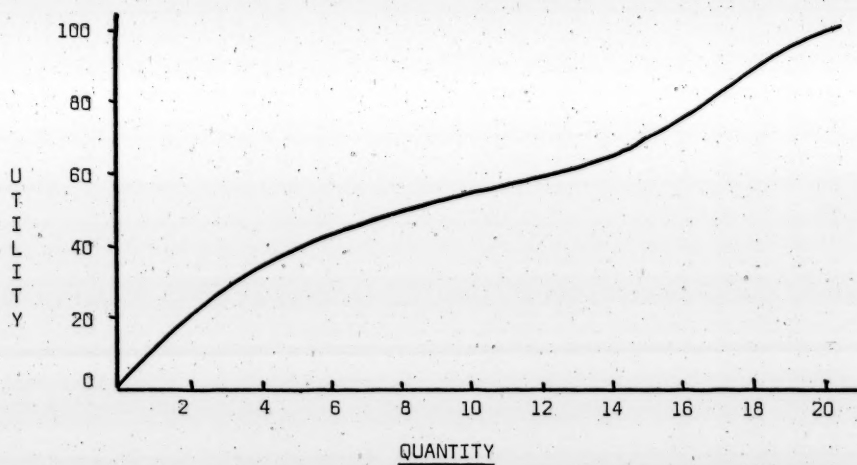


FIGURE 1.7q UTILITY CURVE FOR QUANTITY OF CLUSTER
MEDICATIONS (Intensity 7)

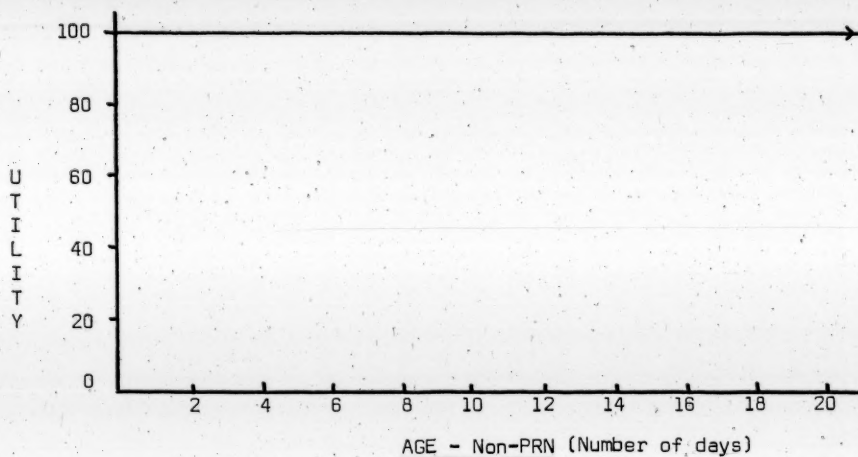


FIGURE 1.8a UTILITY CURVE FOR AGE - Non-PRN OF CLUSTER
ANCILLARY DIAGNOSTIC (Intensities 1, 3, 5)

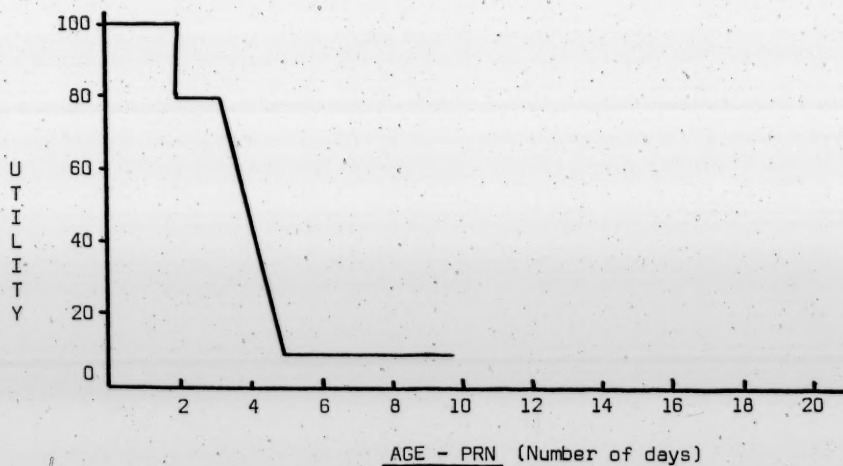


FIGURE 1.8a UTILITY CURVE FOR AGE - PRN OF CLUSTER
ANCILLARY DIAGNOSTIC (Intensities 1, 3, 5)

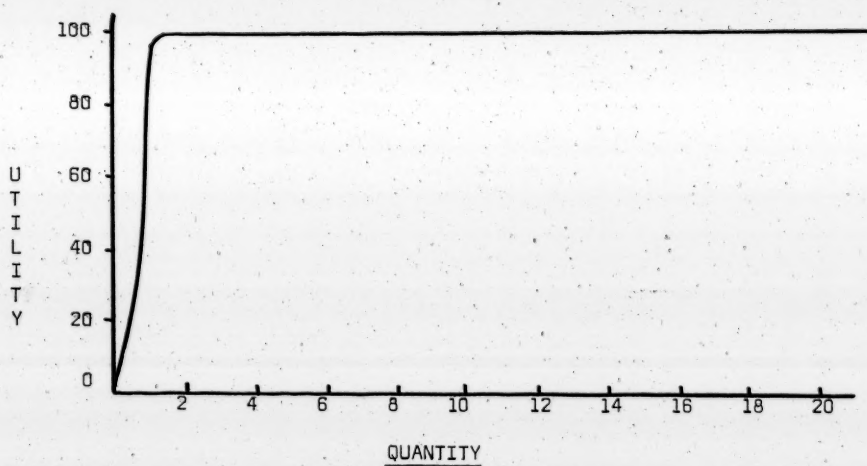


FIGURE 1.8q UTILITY CURVE FOR QUANTITY OF CLUSTER
ANCILLARY DIAGNOSTIC (Intensities 1, 3, 5)

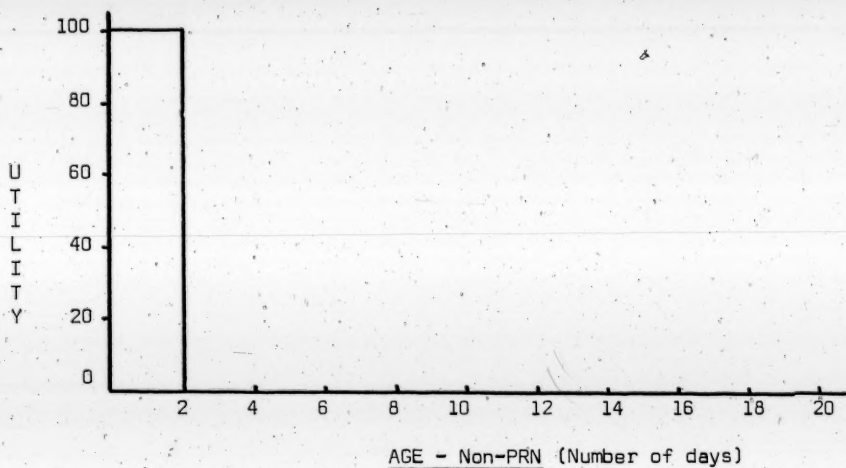


FIGURE 1.9a UTILITY CURVE FOR AGE - Non-PRN OF CLUSTER
ANCILLARY DIAGNOSTIC (Intensity 7)

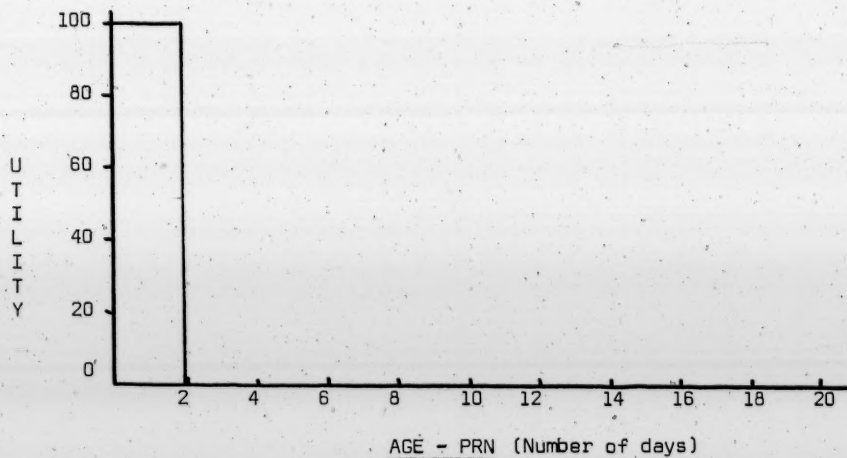


FIGURE 1.9a UTILITY CURVE OF AGE - PRN OF CLUSTER
ANCILLARY DIAGNOSTIC (Intensity 7)

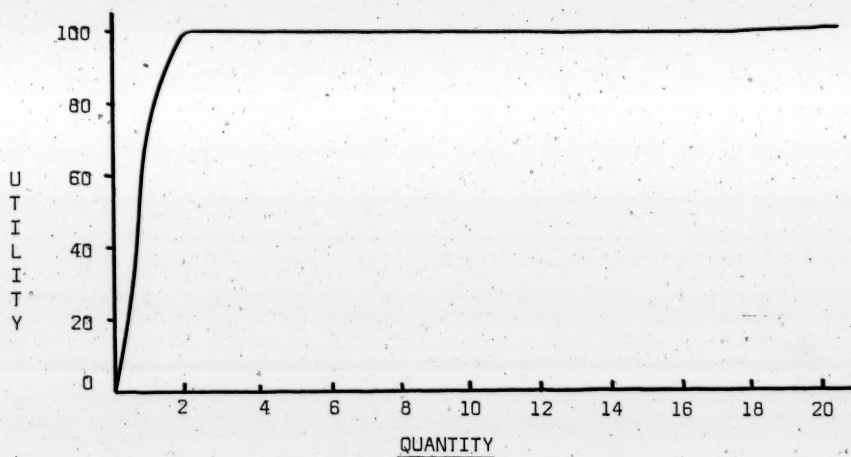


FIGURE 1.9q UTILITY CURVE FOR QUANTITY OF CLUSTER
ANCILLARY DIAGNOSTIC (Intensity 7)

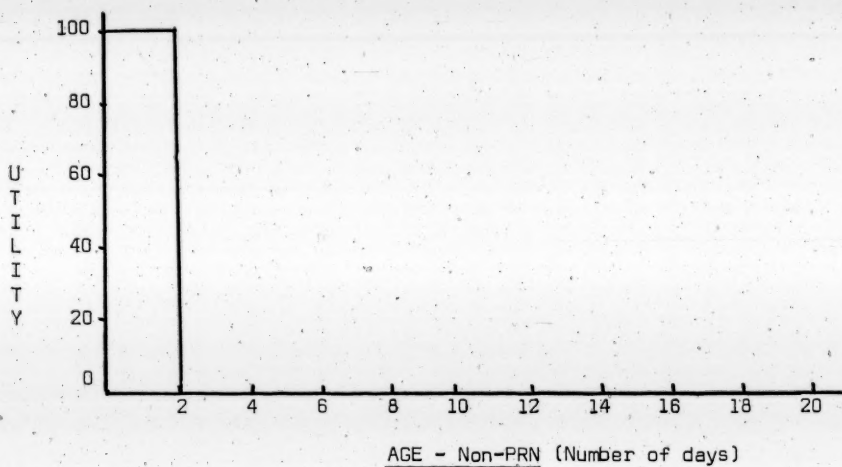


FIGURE 1.10a UTILITY CURVE FOR AGE -Non-PRN OF CLUSTER
ANCILLARY DIAGNOSTIC (Intensity 9)

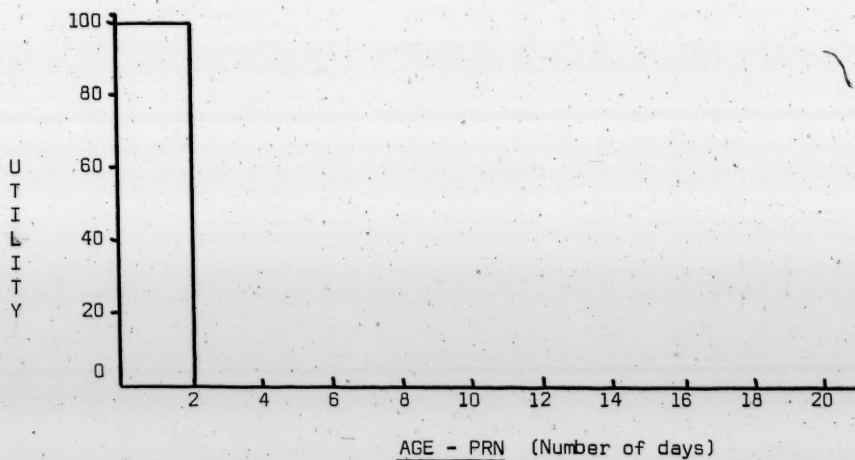


FIGURE 1.10a UTILITY CURVE FOR AGE - PRN OF CLUSTER
ANCILLARY DIAGNOSTIC (Intensity 9)

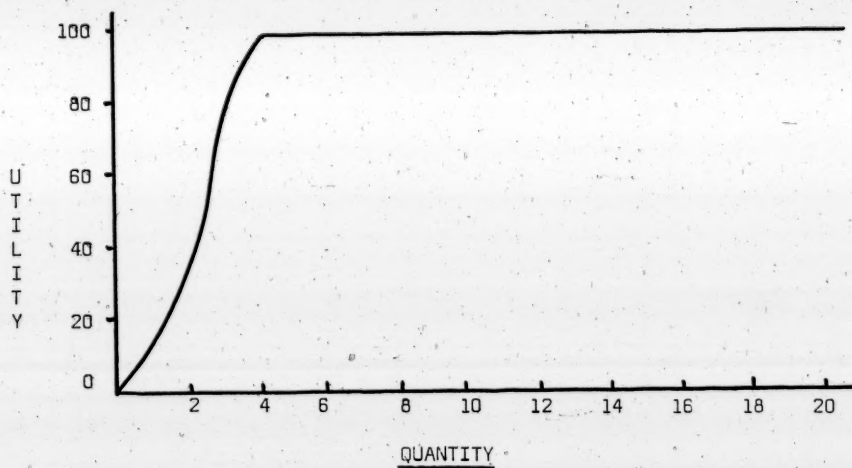


FIGURE 1.10_q UTILITY CURVE FOR QUANTITY OF CLUSTER
ANCILLARY DIAGNOSTIC (Intensity 9)

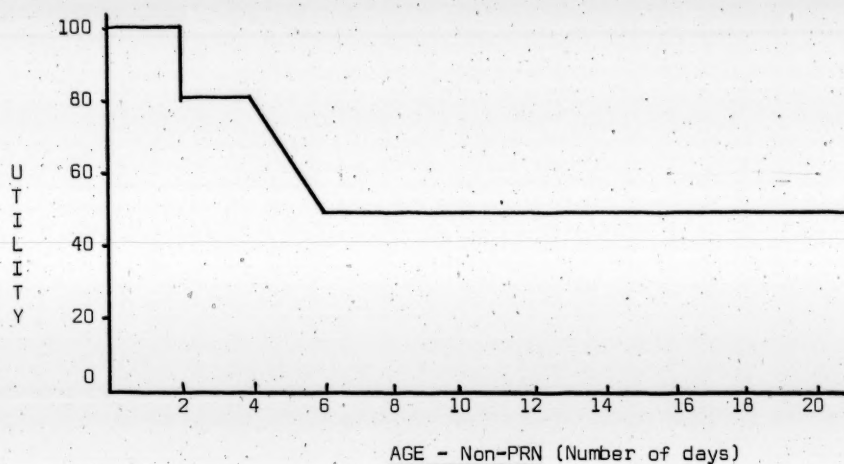


FIGURE 1,11a UTILITY CURVE FOR AGE - Non-PRN OF CLUSTER
ANCILLARY THERAPEUTIC (Intensity 1)

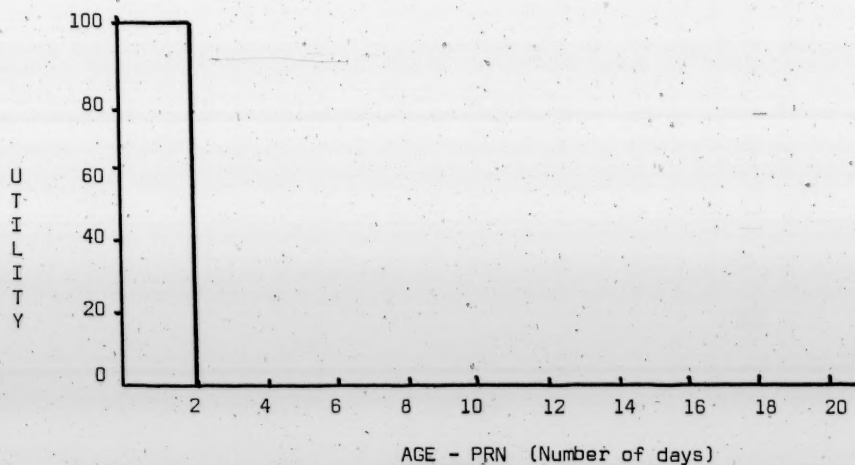


FIGURE 1,11a UTILITY CURVE FOR AGE - PRN OF CLUSTER
ANCILLARY THERAPEUTIC (Intensity 1)

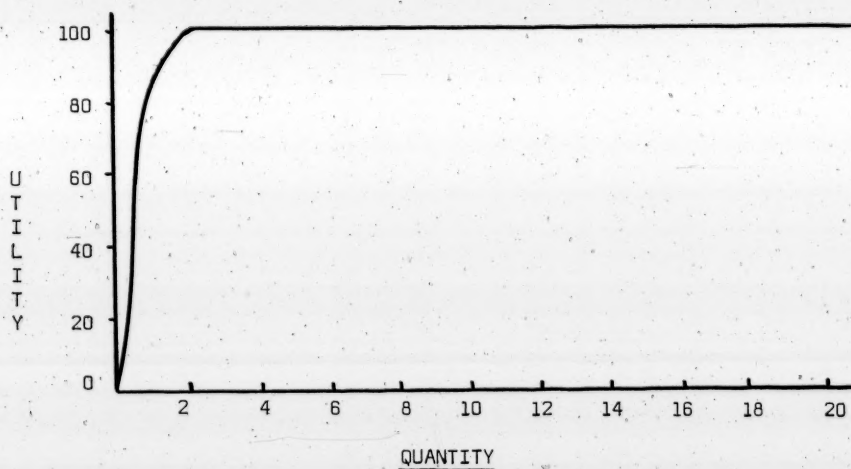


FIGURE 1.11q UTILITY CURVE FOR QUANTITY OF CLUSTER
ANCILLARY THERAPEUTIC (Intensity 1)

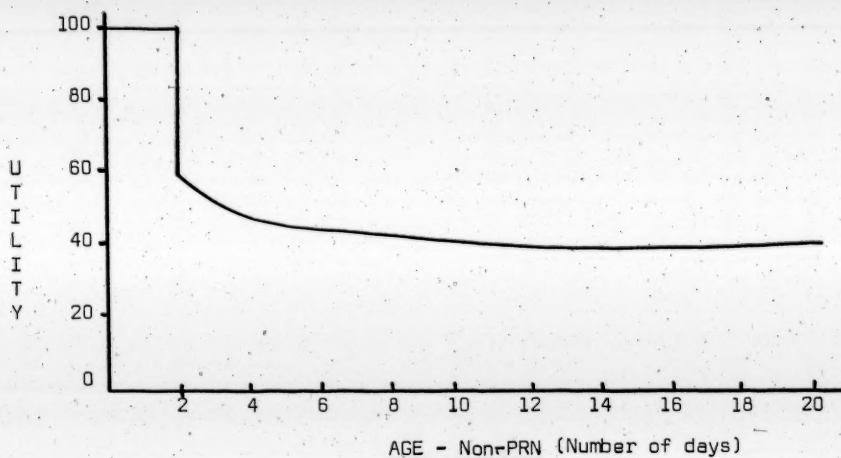


FIGURE 1.12a UTILITY CURVE FOR AGE - Non-PRN OF CLUSTER
ANCILLARY THERAPEUTIC (Intensity 3, Intensity 5)

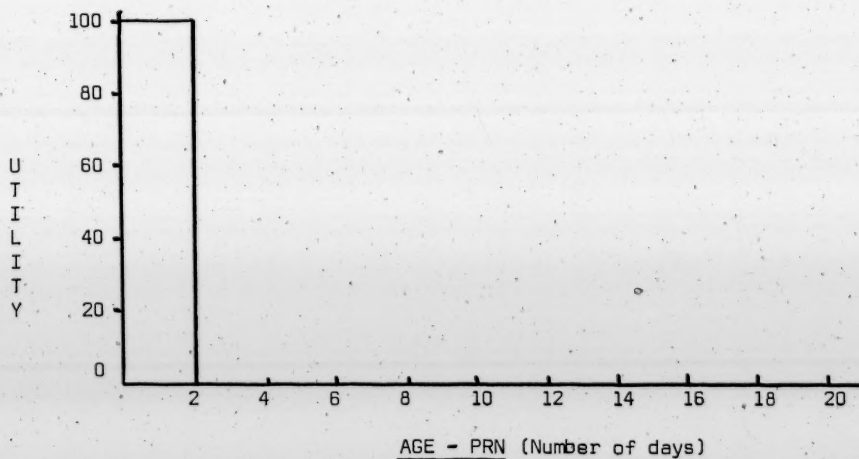


FIGURE 1.12a UTILITY CURVE FOR AGE- PRN OF CLUSTER
ANCILLARY THERAPEUTIC (Intensity 3, Intensity 5)

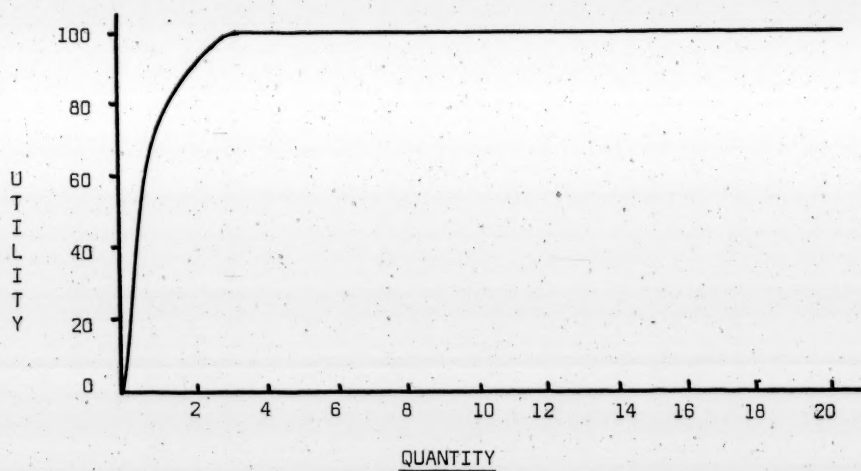


FIGURE 1.12q . UTILITY CURVE FOR QUANTITY OF CLUSTER
ANCILLARY THERAPEUTIC (Intensity 3, Intensity 5)

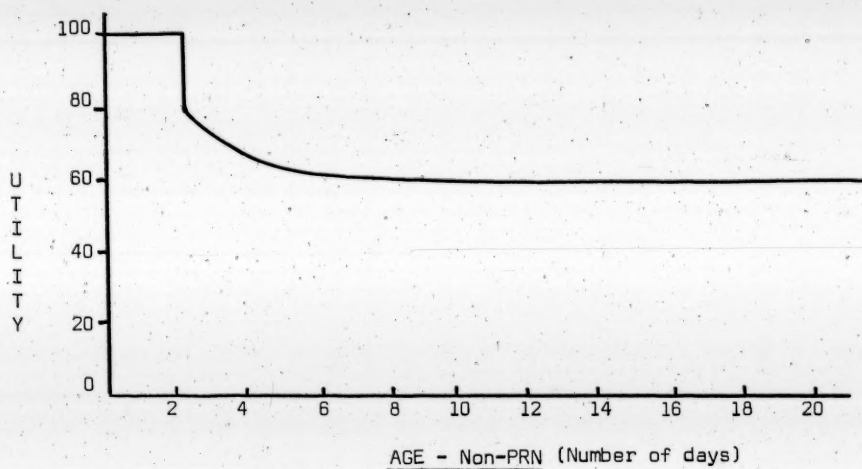


FIGURE 1.13a UTILITY CURVE FOR AGE - Non-PRN OF CLUSTER
ANCILLARY THERAPEUTIC (Intensity 7, Intensity 9)

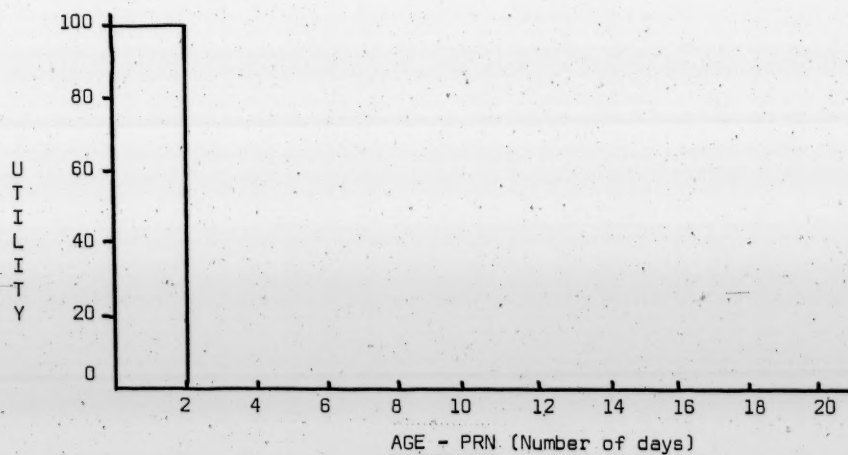


FIGURE 1.13a UTILITY CURVE FOR AGE - PRN OF CLUSTER
ANCILLARY THERAPEUTIC (Intensity 7, Intensity 9)

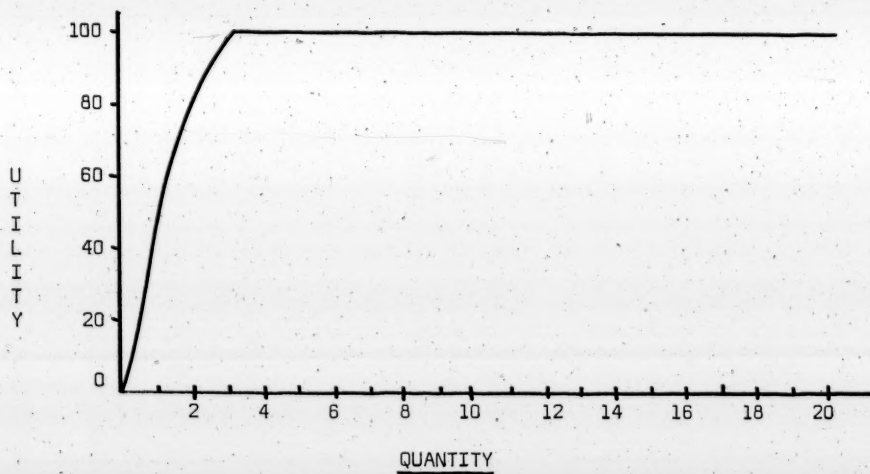


FIGURE 1,13q UTILITY CURVE FOR QUANTITY OF CLUSTER
ANCILLARY THERAPEUTIC (Intensity 7, Intensity 9)

APPENDIX CSTEPWISE VARIABLE SELECTION

PLEASE NOTE:

Appendix C is a computer
print-out. Type is light and
indistinct. Filmed in the
best way possible.

University Microfilms

PROGRAM REVISED JULY 7, 1975
MANUAL DATE -- 1975

BDP7M -- STEPWISE DISCRIMINANT ANALYSIS.
HEALTH SCIENCES COMPUTING FACILITY
UNIVERSITY OF CALIFORNIA, LOS ANGELES

IN THIS VERSION OF BDP7M

-- SUBPROBLEMS ARE NOT PERMITTED.
-- GROUP CODES OR COMMENTS MUST BE STATED.

PROGRAM CONTROL INFORMATION

PROB TITLE = 'DISCRIMINANT FUNCTION FOR UTILIZATION REVIEW.'./

INPUT VARIABLE = 32.

UNIT = 9.

CASE = 715.
FORMAT = '1//AT,3X,FI,0,30(IX,FI,0)'.
GROUP = 2./

VARIABLE GROUPING = JUDGMENT.

NAME = PATIENT, JUDGMENT, N13H, N13M, N5H, N5M, N7H, N7M,
M13H, M13M, M35H, M35M, M7H, M7M,
O135H, O135M, O75H, O75M, O719H, O719M, TH1H, TH1M,
TH35H, TH35M, TH79H, TH79M, HOSP, DISC, M013, M0579.

LABEL = PATIENT.

USE = 2 TO 29, 31, 32./

GROUP CODES = 3, 1.

NAMES ARE SELECT, APPROX.

PRIOR = .55, .45./

PRINT STEP. CLASS = 3 TO 32./

PLOT CAMP./

END

PROBLEM TITLE DISCRIMINANT FUNCTION FOR UTILIZATION REVIEW.

NUMBER OF VARIABLES TO READ IN. 32

NUMBER OF VARIABLES ADDED BY TRANSFORMATIONS. 0

TOTAL NUMBER OF VARIABLES. 32

NUMBER OF CASES TO READ IN. 715

CASE LABELING VARIABLES. PATIENT

LIMITS AND MISSING VALUE CHECKED BEFORE TRANSFORMATIONS

PLANKS ARE. ZEROS

INPUT UNIT NUMBER. 8

RECORD INPUT UNIT PRIOR TO READING. YES

YES

INPUT FORMAT

1//AT,3X,FI,0,30(IX,FI,0)1

VARIABLES TO BE USED

7 1274

12 M35M

17 O135H

23 TH1H

27 TH79H

3,010

F-TO-ENTER

F-TO-REMOVE

1

3,096

1

1

4	N13H	5	M5H	6	N5M
9	M13H	10	M13M	11	M35H
14	M35M	15	M7H	21	M7M
19	O75H	20	O75M	21	O719H
24	TH1H	25	TH35H	26	TH35M
29	TH79H	31	M013	32	M0579

MAXIMUM NUMBER OF STEPS. . . 14
PRIOR PROBABILITIES. . . 0.55000 0.45000

REFORM TRANSFORMATION
MINIMUM MAXIMUM MISSING
LIMIT LIMIT CODE

VARIABLE
NO. NAME

2 JUDGMENT

INTERVAL RANGE
GREATER LESS THAN
THAN OR EQUAL TO

CATEGORY
CODE NAME

0.0000 SELECT
1.00000 APPROX

NUMBER OF CASES READ. 715

STANDARD DEVIATIONS

VERTICAL	GROUP	SELECT	ADDDO	ALL GPS
2 JUDGMENT		0.0	0.0	0.0
3 M13H		0.15737	0.39684	0.29118
4 M13M		0.30968	0.29071	0.30126
5 H2H		0.26619	0.45175	0.35762
6 H2M		0.13535	0.17364	0.14759
7 M2H		0.08726	0.16484	0.12824
8 M2M		0.17145	0.30585	0.20585
9 M13H		0.29629	0.49291	0.32950
10 M13M		0.12292	0.07856	0.10523
11 M35H		0.32922	0.37092	0.34815
12 M35M		0.28193	0.15404	0.23625
13 M35H		0.51635	0.50065	0.55536
14 M35M		0.25356	0.17349	0.22101
15 M2H		0.36774	0.47383	0.37411
16 M2M		0.49302	0.68988	0.49436
17 M135H		0.11350	0.21732	0.17598
18 M135M		0.0	0.07857	0.05280
19 M75H		0.27021	0.35809	0.31816
20 M75M		0.25786	0.29501	0.27526
21 M71H		0.30771	0.48556	0.43463
22 M71M		0.37234	0.43934	0.40400
23 M11H		0.05051	0.0	0.03740
24 M11M		0.02202	0.05564	0.03739
25 M435H		0.17202	0.74134	0.18600
26 M435M		0.14109	0.26261	0.18600
27 M72H		0.53393	0.53803	0.53803
28 M72M		0.36776	0.30931	0.30931
29 M05H		0.11736	0.21566	0.25727
30 M05M		0.0	0.36227	0.25727
31 M013		0.0	0.05564	0.03739
32 M0570		0.08726	0.09607	0.09134

PAGE 4

MEANS/ST.DEVS.

VARIABLE	GROUP =	SELF	ADPRP	ALL CPS.
2 JUDGMENT	0.0	0.0	0.0	0.0
3 M134	0.15159	0.49140	0.33063	0.33063
4 M136	0.34598	0.31860	0.33426	0.33426
5 M5H	0.28781	0.66378	0.49078	0.49078
6 M5H	0.16370	0.15122	0.15122	0.15122
7 M7H	0.08771	0.15904	0.13087	0.13087
8 M7H	0.76104	0.02034	0.33039	0.33039
9 M131H	0.32462	0.07881	0.61176	0.61176
10 M131H	0.37107	0.24238	0.40633	0.40633
11 M35H	0.30779	0.16904	0.40574	0.40574
12 M35H	0.52947	0.27705	0.25656	0.25656
13 M35H	0.27164	0.17847	0.74643	0.74643
14 M35H	0.40368	0.50599	0.23416	0.23416
15 M7H	1.10662	1.23238	0.48235	0.48235
16 M7H	0.13467	0.22794	1.16277	1.16277
17 M135H	0.0	0.07881	0.18279	0.18279
18 M135H	0.29267	0.43737	0.05298	0.05298
19 M7SH	0.27703	0.32533	0.36466	0.36466
20 M7SH	0.47374	0.77788	0.29979	0.29979
21 M15H	0.44528	0.59193	0.62427	0.62427
22 M15H	0.05051	0.0	0.51582	0.51582
23 TH1H	0.0	0.05564	0.03739	0.03739
24 TH1H	0.12482	0.25652	0.03740	0.03740
25 TH15H	0.22541	0.23534	0.19550	0.19550
26 TH15H	0.24354	0.26329	0.23534	0.23534
27 TH15H	0.40368	0.23534	0.23534	0.23534
28 M15H	0.1332	0.62731	0.23909	0.23909
29 M15H	0.0	0.05564	0.03740	0.03740
30 M15H	0.08771	0.09668	0.03187	0.03187
31 M15H	0.08771	0.09668	0.03187	0.03187
32 M15H	0.08771	0.09668	0.03187	0.03187

PAGE 5

STEP NUMBER	VARIABLE	F TO FORCE RE-DOE LEVEL	F TO FORCE ENTER LEVEL	TOLERANCE
0		0	0	
1	3 R134	1 713	1	1.000000
2	4 R134	0.396	1	1.000000
3	5 R54	69.297	1	1.000000
4	6 R54	1.280	1	1.000000
5	7 R74	15.138	1	1.000000
6	8 R74	11.180	1	1.000000
7	9 R114	11.128	1	1.000000
8	10 R134	2.532	1	1.000000
9	11 R35M	10.994	1	1.000000
10	12 R35M	62.155	1	1.000000
11	13 R35M	5.211	1	1.000000
12	14 R35M	5.186	1	1.000000
13	15 R74	2.011	1	1.000000
14	17 D135H	5.738	1	1.000000
15	18 D135H	2.435	1	1.000000
16	19 D75H	11.736	1	1.000000
17	20 D75H	1.408	1	1.000000
18	21 D719H	35.292	1	1.000000
19	22 D719H	9.637	1	1.000000
20	23 H114	0.923	1	1.000000
21	24 H114	1.716	1	1.000000
22	25 H135H	11.120	1	1.000000
23	26 H135H	0.064	1	1.000000
24	27 H179M	12.547	1	1.000000
25	28 H179M	53.977	1	1.000000
26	29 H059	1.214	1	1.000000
27	31 H013	0.056	1	1.000000
28	32 H0579			

STEP NUMBER 2
VARIABLE ENTERED 20 WOSP

VARIABLE	F TO FORCE REMOVE LEVEL	DF	F TO FORCE ENTER LEVEL	TOLERANCE
2 M13H	129.215	1	43.633	0.998478
20 WOSP	70.316	1	0.198	0.999285
			51.280	0.956776
			7.125	0.684743
			4.258	0.498952
			15.443	0.996361
			0.137	0.997023
			7.592	0.999140
			40.357	0.953115
			5.752	0.997078
			14.472	0.976660
			1.758	0.997690
			7.777	0.996547
			2.303	0.998929
			14.138	0.996537
			0.071	0.988017
			19.678	0.981862
			3.110	0.957247
			0.479	0.999906
			2.471	0.997659
			4.203	0.979529
			0.558	0.997307
			1.071	0.996215
			14.369	0.996982
			0.152	0.999001
			0.353	0.994082

U-STATISTIC OF WILKS' LAMBDA 0.7048133 DEGREES OF FREEDOM 2 1 713
APPROXIMATE F-STATISTIC 26.446 DEGREES OF FREEDOM 2.00 712.00

F - MATRIX DEGREES OF FREEDOM = 2 712

APPROX SELECT
26.45

CLASSIFICATION FUNCTIONS

VARIABLE	GROUP =	SELECT	APPROX
2 M13H	0.54301		2.00561
20 WOSP	0.34473		3.02076
CONSTANT	-0.63164		-1.63060

STEP NUMBER 3
VARIABLE ENTERED 5 NCH

VARIABLE	F TO ENTER	DEGREES OF FREEDOM	F TO FORCE	ENTER	THRESHOLD
5 NCH	31.713	1	1.710	31.762	0.98930
6 MICH	32.711	1	0.740	0.94032	0.98432
29 HCHSP	33.113	1	0.740	0.94032	0.98432
7 NCH	34.113	1	0.740	0.94032	0.98432
8 NCH	35.113	1	0.740	0.94032	0.98432
9 NCH	36.113	1	0.740	0.94032	0.98432
10 NCH	37.113	1	0.740	0.94032	0.98432
11 NCH	38.113	1	0.740	0.94032	0.98432
12 NCH	39.113	1	0.740	0.94032	0.98432
13 NCH	40.113	1	0.740	0.94032	0.98432
14 NCH	41.113	1	0.740	0.94032	0.98432
15 NCH	42.113	1	0.740	0.94032	0.98432
16 NCH	43.113	1	0.740	0.94032	0.98432
17 NCH	44.113	1	0.740	0.94032	0.98432
18 NCH	45.113	1	0.740	0.94032	0.98432
19 NCH	46.113	1	0.740	0.94032	0.98432
20 NCH	47.113	1	0.740	0.94032	0.98432
21 NCH	48.113	1	0.740	0.94032	0.98432
22 NCH	49.113	1	0.740	0.94032	0.98432
23 NCH	50.113	1	0.740	0.94032	0.98432
24 NCH	51.113	1	0.740	0.94032	0.98432
25 NCH	52.113	1	0.740	0.94032	0.98432
26 NCH	53.113	1	0.740	0.94032	0.98432
27 NCH	54.113	1	0.740	0.94032	0.98432
28 NCH	55.113	1	0.740	0.94032	0.98432
29 NCH	56.113	1	0.740	0.94032	0.98432
30 NCH	57.113	1	0.740	0.94032	0.98432
31 NCH	58.113	1	0.740	0.94032	0.98432
32 NCH	59.113	1	0.740	0.94032	0.98432

U-STATISTIC OR WILKS' LAMBDA 0.739017 DEGREES OF FREEDOM 3 1 713
APPROXIMATE F-STATISTIC 95.932 DEGREES OF FREEDOM 3.00 711.00

F - MATRIX DEGREES OF FREEDOM = 3 711

APPROX SELECT
95.93

CLASSIFICATION FUNCTIONS

VARIABLE	GROUP =	SELECT	APPROX
5 NCH	0.51713	2.20657	
6 MICH	0.50303	2.62837	
29 HCHSP	0.44581	3.44586	
CONSTANT	-0.64473	-1.94528	

PAGE 9

CLASSIFICATION MATRIX

GROUP	PERCENT CORRECT	NUMBER OF CASES CLASSIFIED INTO GROUP -	
		SELECT	APPROP
SELECT	81.6	320	72
APPROP	65.3	112	211
TOTAL	74.3	432	283

JACKKNIFE CLASSIFICATION

GROUP	PERCENT CORRECT	NUMBER OF CASES CLASSIFIED INTO GROUP -	
		SELECT	APPROP
SELECT	81.6	320	72
APPROP	65.3	112	211
TOTAL	74.3	432	283

STEP NUMBER 4
VARIABLE ENTERED 3 N13H

VARIABLE	F TO FORCE RE-DOVE LEVEL	F TO FORCE ENTER LEVEL	TOLERANCE
3 N13H	1 710	1 709	
5 N5H	41.762	0.380	0.982963
9 P13H	49.278	1.051	0.987923
29 H0SP	95.704	1.045	0.584585
	78.522	5.155	0.562387
		0.222	0.996519
		0.961	0.995073
		0.952	0.995073
		2.596	0.911366
		2.596	0.911366
		2.707	0.967037
		2.717	0.991558
		4.190	0.991094
		2.243	0.996893
		14.823	0.995075
		0.272	0.986661
		11.357	0.972102
		2.692	0.957039
		0.352	0.990852
		3.241	0.996361
		1.027	0.968423
		1.527	0.992392
		0.239	0.990828
		9.694	0.993138
		0.302	0.983855
		0.937	0.993922

J-STATISTIC OR WILKS' LAMBDA 0.7024760 DEGREES OF FREEDOM 4 1 713
ADJUSTED P-STATISTIC 75.178 DEGREES OF FREEDOM 4.00 710.00

F - WAT01X DEGREES OF FREEDOM = 4 710

SELECT
75.18

APPROX

CLASSIFICATION FUNCTIONS

VARIABLE	GROUP =	SELECT	APPROX
3 N13H	0.20409		1.91749
5 N5H	0.49862		2.03263
9 P13H	0.59001		2.50006
29 H0SP	0.44570		3.44545
CONSTANT	-0.45049		-2.00007

CLASSIFICATION MATRIX			
GROUP	PERCENT CORRECT	NUMBER OF CASES CLASSIFIED INTO GROUP -	
		SELECT	APPROP
SELECT	79.3	313	76
APPROP	70.6	95	228
TOTAL	75.7	408	307

JACKKNIFE CLASSIFICATION

GROUP	PERCENT CORRECT	NUMBER OF CASES CLASSIFIED INTO GROUP -	
		SELECT	APPROP
SELECT	79.3	313	76
APPROP	70.6	95	228
TOTAL	75.7	408	307

STEP NUMBER 5
VARIABLE ENTERED 13 M35PH

VARIABLE	F TO FREE RECODE LEVEL	F TO FREE ENTER LEVEL	TOLERANCE
OF = 1 730			
3 N13H	28.460	1	0.971303
5 N5H	24.350	1	0.984107
9 M13H	70.960	1	0.981036
13 M35PH	25.346	1	0.955945
29 M0SP	67.522	1	0.995106
			0.989908
			0.989452
			0.967344
			0.931771
			0.900225
			0.887438
			0.982002
			0.964633
			0.985242
			0.954084
			0.957019
			0.999582
			0.995213
			0.967310
			0.970040
			0.990823
			0.980891
			0.983650
			0.991590

U-STATISTIC OR WILKS' LAMBDA 0.6777679 DEGREES OF FREEDOM 5 1 713
APPROXIMATE F-STATISTIC 67.416 DEGREES OF FREEDOM 5.00 709.00

F - MATRIX DEGREES OF FREEDOM = 5 709

APPROX SELECT
67.42

CLASSIFICATION FUNCTIONS

VARIABLE	GROUP =	SELECT	APPROX
3 N13H	0.15395	1.8073	
5 N5H	0.24474	1.51399	
9 M13H	0.46481	2.36467	
13 M35PH	1.30935	2.05987	
29 M0SP	0.67106	3.90501	
CONSTANT	-0.74655	-2.40088	

CLASSIFICATION MATRIX

GROUP	PERCENT CORRECT	NUMBER OF CASES CLASSIFIED INTO GROUP - SELECT	SELECT	APPROX
SELECT	84.9	333	59	
APPROX	65.3	112	211	
TOTAL	76.1	445	270	

JACKKNIFE CLASSIFICATION

GROUP	PERCENT CORRECT	NUMBER OF CASES CLASSIFIED INTO GROUP - SELECT	SELECT	APPROX
SELECT	94.9	333	59	
APPROX	65.3	112	211	
TOTAL	76.1	445	270	

STEP NUMBER 5
VARIABLE ENTERED 19 07SH

VARIABLE	REMOVE LEVEL	F TO FORCE	VARIABLE	F TO FORCE	ENTER LEVEL	TOLERANCE
1 N13H	OF=	1.070	4 N13M	OF=	1.707	0.948102
5 N13H	27.275	1	6 N13M	0.494	1	0.984006
9 N13H	24.822	1	7 N13H	1.574	1	0.980976
13 N13H	25.714	1	8 N13M	3.657	1	0.955770
19 07SH	16.443	1	10 N13M	0.077	1	0.995103
29 07SH	89.425	1	11 N13H	2.139	1	0.988608
			12 N13M	2.703	1	0.964358
			13 N13H	0.477	1	0.966358
			15 N13H	3.691	1	0.930770
			16 N13H	1.150	1	0.983074
			17 N13H	3.236	1	0.966349
			18 N13H	1.531	1	0.974041
			20 07SH	0.028	1	0.972447
			21 07SH	10.387	1	0.920008
			22 07SH	1.555	1	0.951541
			23 07SH	0.196	1	0.990430
			24 07SH	4.100	1	0.944495
			25 07SH	1.692	1	0.966092
			26 07SH	3.151	1	0.959539
			27 07SH	0.464	1	0.980726
			28 07SH	0.031	1	0.973720
			31 07SH	0.020	1	0.990397
			32 07SH	0.620	1	0.990397

J-S-STATISTIC OR WILKS' LAMBDA 0.6603745 DEGREES OF FREEDOM 6 1 713
 APPROXIMATE F-STATISTIC 60.686 DEGREES OF FREEDOM 6.00 708.00

F - MATRIX DEGREES OF FREEDOM = 6 708

SELECT
 APPROX 60.59

CLASSIFICATION FUNCTIONS

VARIABLE	GROUP =	SELECT	APPROP
3 G13H		0.15630	1.02095
5 K5H		0.77797	1.54367
9 W13H		0.49545	2.43331
13 W35PH		1.00453	2.23066
19 D75H		1.00896	2.26200
20 W5P		0.73573	4.05080
CONSTANT		-0.70727	-2.75483

CLASSIFICATION MATRIX

GROUP	PERCENT CORRECT	NUMBER OF CASES CLASSIFIED INTO GROUP -
SELECT	89.0	SELECT 185
APPROP	62.2	APPROP 122
TOTAL	76.9	571 244

JACKKNIFE CLASSIFICATION

GROUP	PERCENT CORRECT	NUMBER OF CASES CLASSIFIED INTO GROUP -
SELECT	83.2	SELECT 326
APPROP	62.2	APPROP 122
TOTAL	73.7	448 267

VARIABLE	1 TO FORCE RELATIVE LEVEL
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J-STATISTIC OR WILKS' LAMBDA	0.0508121	DEGREES OF FREEDOM	7	1	713
APPROXIMATE F-STATISTIC	54.191	DEGREES OF FREEDOM	7	00	707.00

F - MATRIX DEGREES OF FREEDOM = 7, 707

SELECT
54.19
APPROP

CLASSIFICATION FUNCTIONS

GROUP = SELECT APPROP

VARIABLE	HEIN 3	0.03138	1-60162
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5	MSA	0.16979	1.38983
6	MLM	0.35566	2.19959

Run	Time	Area	Height	Area%	Height%
13	0.35	1.19	1.19	2.42	2.42
19	0.75	0.76	0.76	1.83	1.83

21 0719H	0.94992	1.66785
21 0717H	0.94992	1.66785
20 0719H	0.94992	1.66785

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CLASSIFICATION MATRIX

GROUP	PERCENT CORRECT	NUMBER OF CASES CLASSIFIED INTO GROUP -
SELECT	87.2	342
APPROP	66.9	107
TOTAL	79.0	449

JACKKNIFE CLASSIFICATION

GROUP	PERCENT CORRECT	NUMBER OF CASES CLASSIFIED INTO GROUP -
SELECT	87.2	342
APPROP	66.9	107
TOTAL	79.0	449

STEP NUMBER 8
VARIABLE ENTERED 22 07104

VARIABLE	F TO FORCE REMOVE LEVEL	DF	VARIABLE	F TO FORCE ENTER LEVEL	TOLERANCE
3 M13H	23.153	1	4 M13M	0.392	1
5 N5H	15.931	1	6 N5M	0.644	1
9 M13H	59.475	1	7 N7H	0.931	1
13 M39PH	33.957	1	8 M7M	2.961	1
19 M7SH	9.671	1	10 M13M	0.311	1
21 M7E94	15.661	1	11 M35MH	1.232	1
22 07104	6.877	1	12 M35M	0.270	1
29 M05H	74.517	1	13 M35M	0.210	1
			15 M7M	2.557	1
			16 M7M	0.926	1
			17 M13H	2.387	1
			18 M13M	0.963	1
			19 M13H	1.318	1
			20 M7SH	0.705	1
			23 M14	0.112	1
			24 M14	3.186	1
			25 M13H	1.334	1
			26 M13M	3.211	1
			27 M79H	0.067	1
			28 M79M	5.039	1
			31 M013	0.019	1
			32 M0579	0.533	1
U-STATISTIC OR WILK'S LAMBDA	0.6446246	DEGREES OF FREEDOM	8	1	713
APPROXIMATE F-STATISTIC	49.651	DEGREES OF FREEDOM	8	0.00	706.00
F - MATRIX	DEGREES OF FREEDOM =	8	706		
APPROP	SELECT				
43.65	43.65				

CLASSIFICATION FUNCTIONS

VARIABLE	GROUP =	SELECT	APPROX
3 M13H	-0.02102	1.52710	
5 M4H	0.09701	1.20633	
6 M13H	0.32227	2.14071	
13 M3PH	1.23325	2.48714	
19 D7SH	0.47311	1.42655	
21 D71SH	1.50392	2.45135	
22 D71SH	1.57716	2.26262	
29 M0SP	0.33264	3.50037	
CONSTANT	-1.09246	-3.33377	

CLASSIFICATION MATRIX

GROUP	PERCENT CORRECT	NUMBER OF CASES CLASSIFIED INTO GROUP -
SELECT	87.2	362
APPROP	67.8	104
TOTAL	78.5	466

JACKKNIFE CLASSIFICATION

GROUP	PERCENT CORRECT	NUMBER OF CASES CLASSIFIED INTO GROUP -
SELECT	87.2	342
APPROP	67.8	194
TOTAL	78.5	466

STEP NUMBER 3
VARIABLE ENTERED 28 IN708

VARIABLE	F TO FORCE REMOVED LEVEL	DEG	VARIABLE	F TO FORCE ENTER LEVEL	INTEPAIFE
3 M13H	22.517	1	4 M13H	0.869	0.945633
5 N5H	19.293	1	6 N5H	0.778	0.979477
9 M13H	91.533	1	7 N7H	0.706	0.975625
13 M35PH	0.976	1	8 N7H	2.564	0.952095
19 D7SH	14.262	1	10 M13H	0.508	0.985694
21 D710H	5.506	1	11 M35H	1.270	0.981442
22 D710H	5.083	1	12 M35H	1.403	0.956164
28 TH79H	76.602	1	14 M35H	0.405	0.956778
29 H0SP			15 M7H	2.150	0.921151
			16 M7H	0.473	0.967271
			17 O135H	2.575	0.962410
			18 O135H	1.717	0.958627
			20 D754	0.004	0.908326
			23 TH14	0.143	0.990351
			24 TH14	3.199	0.964342
			25 TH35H	3.135	0.974744
			26 TH35H	0.007	0.983469
			27 TH29H	0.012	0.965369
			31 M013	0.585	0.987062
			32 M0579		
U-STATISTIC OF WILCOX LAMDA	0.6400047	DEGREES OF FREEDOM	9	1	713
APPROXIMATE P-STATISTIC	44.062	DEGREES OF FREEDOM	9	0.00	705.00

F - MATRIX DEGREES OF FREEDOM = 9 705

APPROX SELECT
44.06

CLASSIFICATION FUNCTIONS

VARIABLE	GROUP =	SELECT	APPROX
3 M13H	0.01491		1.54914
5 N5H	0.13149		1.30848
9 M13H	0.21118		2.07258
13 M35PH	1.39771		2.39622
19 D7SH	0.42366		2.50965
21 D710H	1.56654		2.25923
22 D710H	1.89824		1.12753
28 TH79H	1.93829		3.40532
29 H0SP	0.30811		
CONSTANT	-1.19324		-3.30049

CLASSIFICATION MATRIX

GROUP	PERCENT CORRECT	NUMBER OF CASES CLASSIFIED INTO GROUP -	
		SELECT	APPROP
SELECT	87.5	343	49
APPROP	66.9	137	215
TOTAL	78.2	480	265

JACKKNIFE CLASSIFICATION

GROUP	PERCENT CORRECT	NUMBER OF CASES CLASSIFIED INTO GROUP -	
		SELECT	APPROP
SELECT	86.2	338	54
APPROP	66.9	107	215
TOTAL	77.5	445	270

SUMMARY TABLE

STEP NUMBER	VARIABLE ENTERED	VARIABLE REMOVED	F VALUE TO ENTER OR REMOVE	NUMBER OF VARIABLES INCLUDED	U-STATISTIC	APPROXIMATE P-STATISTIC
1	9 21314		111.1937	1	0.9651	111.189
2	23 00SP		70.0152	2	0.7868	96.446
3	5 96H		51.2718	3	0.7339	85.932
4	3 913H		31.7618	4	0.7025	75.178
5	13 235PH		25.8460	5	0.6778	67.416
6	19 07SH		18.6477	6	0.6604	60.686
7	21 0719H		10.3875	7	0.6508	54.191
8	23 0719H		6.7760	8	0.6446	48.651
9	23 1070H		5.0889	9	0.6400	44.062

APPENDIX DSEVEN VARIABLE LOGISTICFUNCTION on ESTIMATION SET

LYNDON SCHOOL OF HYGIENE AND TROPICAL MEDICINE

QUANTAL REGRESSION PROGRAM

WRITTEN BY D. CLAYTON, APR. 1969

JOSE DOUBLE PRECISION VERSION, JULY 1973

PROBLEM 1

THIS PROGRAM TREATS 715 CASES

9 VARIABLES ARE READ IN, AND 0 NEW VARIABLES ARE CREATED

THE DEPENDENT RATE VARIABLE IS VARIABLE 1

DATA IS ON INPUT CHANNEL 9

NUMBER OF TRIALS PER CASE IS CONSTANT - 1

NUMBER OF VARIABLE FORMAT CARDS FOR INPUT - 1

FORMAT OF INPUT RECORDS - (//10X,F1.0,2(1X,F1.0,2X),5X,F1.0,7X,F1.0,11X,F1.0,3X,F1.0,15X,F1.0)

LIKELIHOOD RATIO CHI-SQUARE ANALYSIS

DUE TO REGRESSION	8	309.701
ABOUT REGRESSION	707	681.500
TOTAL	715	991.200

CHI-SQUARE DUE TO REGRESSION MAY BE PARTITIONED AS FOLLOWS

DUE TO CONSTANT	1	6.669
DUE TO INCLUSION OF INDEP. VARIABLES	7	303.032
FINAL ITERATION COUNT=	25	

REGRESSION 1

NUMBER OF PARAMETERS 8
 REQ. ACCURACY 0.1E-05
 MAXIMUM ITERATIONS 80
 PRELIMINARY ESTIMATE 0.35E 03
 ITERATION LIMIT AT START 80
 LIMIT INCREMENT 20

VARIABLE	COEFFICIENT	S.D.	T-VALUE	CHANGE IN LAST ITERATION	PARTIAL DERIV. DF - LOG L
2	0.907150 70	0.19310E 00	4.69776	-0.14E-16	0.20E-07
3	0.501080 00	0.13311E 00	4.51568	-0.14E-16	-0.10E-06
4	0.947900 00	0.11665E 00	7.26904	-0.20E-16	-0.49E-07
5	0.573120 00	0.10351E 00	5.53670	-0.14E-16	-0.19E-06
6	0.550650 00	0.14735E 00	3.73704	-0.28E-16	-0.80E-07
7	0.348950 00	0.11134E 00	3.13359	-0.28E-16	-0.12E-06
8	0.176280 01	0.25076E 00	7.02958	-0.22E-15	-0.68E-07
CONSTANT	-0.942470 00	0.80515E-01	-11.70556	0.14E-16	-0.51E-06

87033

2.2.112

4.5.2

7.4.5.12

has not been approved
 what for is it
 what after 12.03.55 sent on

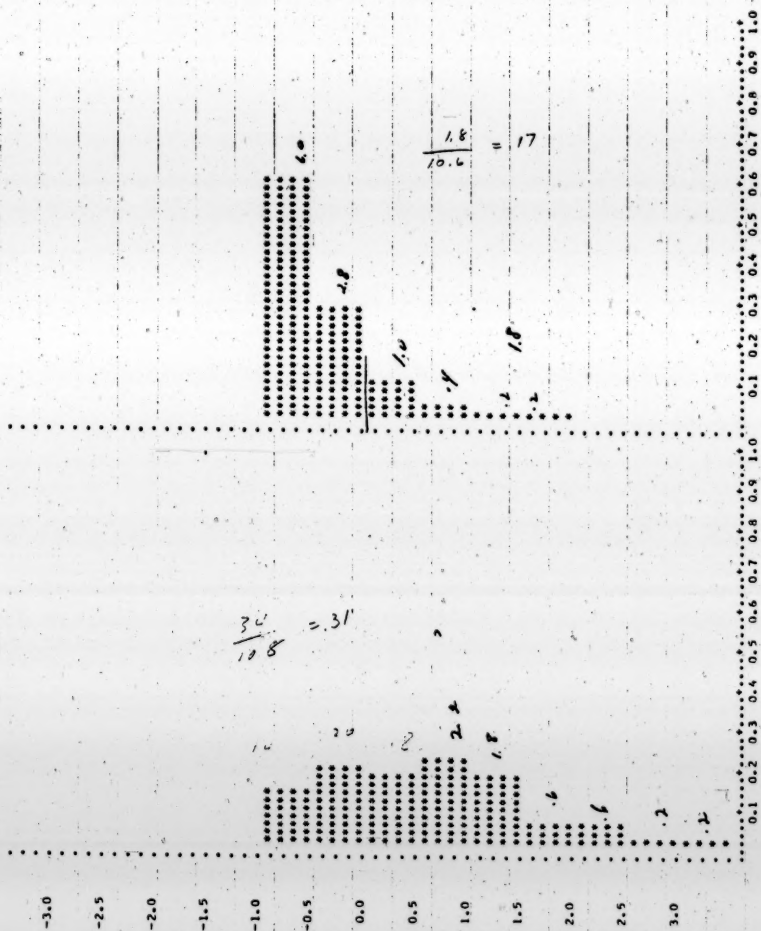
INTERCORRELATION MATRIX OF ESTIMATES OF COEFFICIENTS

1.000					
-0.016	1.000				
0.023	0.739	1.000			
-0.001	-0.161	-0.028	1.000		
0.043	0.053	0.114	0.125	1.000	
-0.061	-0.049	-0.078	0.159	-0.177	1.000
0.029	0.058	0.093	0.126	0.079	0.067
-0.149	-0.186	-0.317	-0.520	-0.294	-0.366
					1.000

PLOT OF DISTRIBUTIONS OF PREDICTED LOGITS

SUCCESSSES
N = 323

FAILURES
N = 392



APPENDIX EINDIVIDUAL RECORDS OF EVALUATION SET
INCLUDING LEVEL OF CARE INDEX

(The Level of Care Index is the value of the 'logit'.
Group Assignment = 0 is equivalent to G_S
Group Assignment = 1 is equivalent to $G_{\bar{S}}$.)

[illegible]

[illegible]

[illegible]

2293267 1122603701 1092449927092443046 0459 35960459 05019
 2293267 2 300049
 229326705 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0
 2293267 JUDGMENT = 0 ASSIGNED TO GROUP 0 LOGIT = -0.0424
 2293267 CLOS 50P AND TSP = 05,06ACTUAL LOS = 040LOS 50P AND TSP = 05,06ACTUAL LOS = 040DISCHARGE ORDER = 1
 2293393 1153505215 092770923309970045 6252659 31036252 66570407089
 2293393 2 300059
 229339305 1 0 1 0 1 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0
 2293393 JUDGMENT = 1 ASSIGNED TO GROUP 1 LOGIT = 0.5107
 2293393 CLOS 50P AND TSP = 07,09ACTUAL LOS = 040LOS 50P AND TSP = 07,09ACTUAL LOS = 040DISCHARGE ORDER = 0
 1293406 191103703 0928109233109620055 8204 9180209 81678816210
 1293406 2 000139
 129340605 1 1 0 0 0 1 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0
 1293406 JUDGMENT = 1 ASSIGNED TO GROUP 1 LOGIT = 0.8126
 1293406 CLOS 50P AND TSP = 09,18ACTUAL LOS = 050LOS 50P AND TSP = 16,21ACTUAL LOS = 050DISCHARGE ORDER = 0
 1293415 1136607073 1092310922209256015 5936 040659365921966 06009
 1293415 2 300049
 129341505 1 0 0 0 0 1 1 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0
 1293415 JUDGMENT = 1 ASSIGNED TO GROUP 1 LOGIT = 0.4785
 1293415 CLOS 50P AND TSP = 05,06ACTUAL LOS = 010LOS 50P AND TSP = 06,09ACTUAL LOS = 010DISCHARGE ORDER = 0
 2293423 1047508791 0927709222100140056 7820 03047828533P 03049
 2293423 2 300099
 229342305 1 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0
 2293423 JUDGMENT = 1 ASSIGNED TO GROUP 0 LOGIT = -0.5935
 2293423 CLOS 50P AND TSP = 01,04ACTUAL LOS = 050LOS 50P AND TSP = 03,04ACTUAL LOS = 050DISCHARGE ORDER = 0
 5293423 1047508791 20430309222100140006 7820 03047820533P 03049
 5293423 2 300099
 529342305 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0
 5293423 JUDGMENT = 0 ASSIGNED TO GROUP 1 LOGIT = 0.3137
 5293423 CLOS 50P AND TSP = 03,04ACTUAL LOS = 080LOS 50P AND TSP = 03,04ACTUAL LOS = 080DISCHARGE ORDER = 0
 1293430 1164408661 21036309222102570115 7820 93056770 06389
 1293430 2 000339
 129343005 1 0 1 0 1 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0
 1293430 JUDGMENT = 1 ASSIGNED TO GROUP 0 LOGIT = -0.0946

1293844	105110101	31007509291101F70097	1099	34101980	06100	
1293844.2					000290	
129384405	0 0 0 0 0 0 3 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0					
1293844	JUDGMENT = 0	ASSIGNED TO GROUP 0	LOGIT = -0.9546			
1293844	CLUS 50P AND 75P = 05.10ACTUAL LOS = 00HLOS 50P AND 75P = 05.10ACTUAL LOS = 00DISCHARGE ORDER = 0					
1293844	1144517053	1100409303101060085	5969	36075936560956798509129		
1293844.2		10035515700911			000100	
129384405	0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0					
1293844	JUDGMENT = 0	ASSIGNED TO GROUP 0	LOGIT = -0.0425			
1293864	CLUS 50P AND 75P = 09.11ACTUAL LOS = 00HLOS 50P AND 75P = 09.11ACTUAL LOS = 00DISCHARGE ORDER = 0					
1293864	111121315	21301493031010620015	5756	33045784	51149087089	
1293864.2		10015114003708			000060	
129386405	1 0					
1293867	JUDGMENT = 1	ASSIGNED TO GROUP 1	LOGIT = 1.1693			
1293867	CLUS 50P AND 75P = 07.09ACTUAL LOS = 01HLOS 50P AND 75P = 07.09ACTUAL LOS = 01DISCHARGE ORDER = 0					
1293899	10624310962	11010609292101320115	7820	03055321	436	10149
1293899.2		1003436	1014		300149	
129389905	1 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0					
1293899	JUDGMENT = 1	ASSIGNED TO GROUP 1	LOGIT = 0.4785			
1293899	CLUS 50P AND 75P = 17.14ACTUAL LOS = 11HLOS 50P AND 75P = 10.14ACTUAL LOS = 11DISCHARGE ORDER = 0					
1293899	10624310962	2130149303101320145	7820	03055321	436	10149
1293899.2		1003436	1014		300149	
129389905	0 0					
1293899	JUDGMENT = 0	ASSIGNED TO GROUP 0	LOGIT = -0.9425			
1293899	CLUS 50P AND 75P = 17.14ACTUAL LOS = 14HLOS 50P AND 75P = 10.14ACTUAL LOS = 14DISCHARGE ORDER = 1					
1293929	1051694221	31007309292100840085	6102	14174109	14179	
1293929.2		100831051008412			300099	
129392905	0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0					
1293929	JUDGMENT = 0	ASSIGNED TO GROUP 0	LOGIT = -0.9425			
1293929	CLUS 50P AND 75P = 14.17ACTUAL LOS = 98HLOS 50P AND 75P = 14.17ACTUAL LOS = 00DISCHARGE ORDER = 0					
1294029	102953244	1011709303102610115	7253	05087253	030	10149
1294029.2		1019330	1014		300269	
129402905	0 0					
1294029	JUDGMENT = 0	ASSIGNED TO GROUP 0	LOGIT = -0.9425			

6294168 JUDGMENT = 0 ASSIGNED TO GROUP 0 LOGIT = -0.9425
 6294168 CLUS 50P AND 75P = 34,06ACTUAL LOS = 070LOS 50P AND 75P = 04,06ACTUAL LOS = 070DISCHARGE ORDER = 1
 3294175 1151508302 11039510025101210075 531 1406531 04069 300130 9
 3294175 JUDGMENT = 0 ASSIGNED TO GROUP 0 LOGIT = -0.9425
 3294175 CLUS 50P AND 75P = 34,06ACTUAL LOS = 070LOS 50P AND 75P = 04,06ACTUAL LOS = 070DISCHARGE ORDER = 0
 1294188 1132598185 21003613025101650015 7020 020456957820024 04079 000140 9
 1294188 JUDGMENT = 1 ASSIGNED TO GROUP 1 LOGIT = 1.7627
 1294188 CLUS 50P AND 75P = 02,04ACTUAL LOS = 010LOS 50P AND 75P = 04,07ACTUAL LOS = 010DISCHARGE ORDER = 0
 1294195 1024633234 31007310036131430046 7253 05087251 06099 000119 9
 1294195 JUDGMENT = 0 ASSIGNED TO GROUP 0 LOGIT = -0.9425
 1294195 CLUS 50P AND 75P = 05,08ACTUAL LOS = 040LOS 50P AND 75P = 06,09ACTUAL LOS = 040DISCHARGE ORDER = 0
 1294278 1146505355 11008410051101320035 218 2201 02046252 68365507089
 1294278 JUDGMENT = 1 ASSIGNED TO GROUP 1 LOGIT = 1.4286
 1294278 CLUS 50P AND 75P = 07,08ACTUAL LOS = 030LOS 50P AND 75P = 07,08ACTUAL LOS = 330DISCHARGE ORDER = 0
 1294307 10685320242 1016509232103160173 1621 06111621 03098115219
 1294307 JUDGMENT = 1 ASSIGNED TO GROUP 0 LOGIT = -0.9425
 1294307 CLUS 50P AND 75P = 15,21ACTUAL LOS = 170LOS 50P AND 75P = 15,21ACTUAL LOS = 170DISCHARGE ORDER = 0
 4293907 10685320242 1019107292103160203 1621 06111621 03098115219
 4293907 JUDGMENT = 1 ASSIGNED TO GROUP 0 LOGIT = -0.9425
 4293907 CLUS 50P AND 75P = 15,21ACTUAL LOS = 200LOS 50P AND 75P = 15,21ACTUAL LOS = 200DISCHARGE ORDER = 0
 1293907 10685320242 11022409292103160233 1621 06111621 03098115219

12964293	1166203034	31007317051100940025	3572	06763572	060	02643
12964293	2	1006360	0304			000136
1296429305	1	1	0	0	0	1
12964293	JUDGMENT = 1	ASSIGNED TO GROUP 1	LOGIT = 0.5378			
12964293	CLOS 50P AND 75P = 03,06ACTUAL LOS = 020LOS 50P AND 75P =	23,047ACTUAL LOS = 020DISCHARGE ORDER = 0				
12964308	1121295405	31007317051101170025	1891140	010318001049684	06079	
12964308	2	1306584	0607			000069
1296430805	1	0	0	1	0	1
12964308	JUDGMENT = 1	ASSIGNED TO GROUP 1	LOGIT = 1.0796			
12964308	CLOS 50P AND 75P = 06,07ACTUAL LOS = 020LOS 50P AND 75P =	95,07ACTUAL LOS = 020DISCHARGE ORDER = 0				
12964321	1133422234	1905113047100730015	7283	05082782	05089	
12964321	2					000037
1296432105	1	0	0	0	1	0
12964321	JUDGMENT = 0	ASSIGNED TO GROUP 1	LOGIT = 0.8048			
12964321	CLOS 50P AND 75P = 05,08ACTUAL LOS = 010LOS 50P AND 75P =	05,08ACTUAL LOS = 010DISCHARGE ORDER = 0				
12964322	1154408316	31007310047100840036	5750	03055750	03059	
12964322	2					000049
1296432205	0	0	0	0	0	0
12964322	JUDGMENT = 0	ASSIGNED TO GROUP 1	LOGIT = 0.1F13			
12964322	CLOS 50P AND 75P = 03,05ACTUAL LOS = 030LOS 50P AND 75P =	03,05ACTUAL LOS = 030DISCHARGE ORDER = 0				
12964377	1080301286	31007310062100730015	1401	885	03051401	885
12964377	2					000015
1296437705	0	0	0	0	0	0
12964377	JUDGMENT = 0	ASSIGNED TO GROUP 0	LOGIT = -0.3694			
12964377	CLOS 50P AND 75P = 03,05ACTUAL LOS = 010LOS 50P AND 75P =	33,05ACTUAL LOS = 010DISCHARGE ORDER = 1				
12964453	1132511046	21015410073102F60005	5176	03052271862034133205076		
12964453	2	122341	05071010	337		000270
1296445305	1	0	1	0	0	0
12964453	JUDGMENT = 1	ASSIGNED TO GROUP 0	LOGIT = -0.9425			
12964453	CLOS 50P AND 75P = 03,05ACTUAL LOS = 000LOS 50P AND 75P =	05,07ACTUAL LOS = 000DISCHARGE ORDER = 0				
12964476	116513223	11017617062101760055	7250	03097740	8130F112169	
12964476	2					000016
1296447605	1	1	0	1	0	0
12964476	JUDGMENT = 1	ASSIGNED TO GROUP 1	LOGIT = 2.3358			

1294476 CLOS 50P AND 75P = 12,16ACTUAL LOS = 060LOS 50P AND 75P = 12,16ACTUAL LOS = 060ISCHARGE ORDER = 0
 4294476 1165112023 21013210062101760075 7550 33007250 31098112159
 4294476 2 10094109811216 000110
 429447605 0 0 1 0 0 1 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0
 4294476 JUDGMENT = 0 ASSIGNED TO GROUP 0 LOGIT = -0.3414
 4294476 CLOS 50P AND 75P = 12,16ACTUAL LOS = 070LOS 50P AND 75P = 12,16ACTUAL LOS = 070ISCHARGE ORDER = 0
 1294476 1177333771 11009510062101320035 486 0710480 07106
 1294476 2 300070
 129447605 0 0 1 0 1 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0
 1294476 JUDGMENT = 0 ASSIGNED TO GROUP 0 LOGIT = -0.3414
 1294476 CLOS 50P AND 75P = 07,10ACTUAL LOS = 030LOS 50P AND 75P = 07,10ACTUAL LOS = 030ISCHARGE ORDER = 0
 4294476 1177333771 1012110062101320065 486 0710480 07109
 4294476 2 000079
 429447605 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 1 0 1 0 0 0 0 0 0
 4294476 JUDGMENT = 0 ASSIGNED TO GROUP 0 LOGIT = -0.5425
 4294476 CLOS 50P AND 75P = 07,10ACTUAL LOS = 060LOS 50P AND 75P = 07,10ACTUAL LOS = 060ISCHARGE ORDER = 0
 3294476 1172101522 11009510062101760036 562P 04065641 04069
 3294476 2 10174262 000110
 329447605 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0
 3294476 JUDGMENT = 0 ASSIGNED TO GROUP 0 LOGIT = -0.5935
 3294476 CLOS 50P AND 75P = 04,06ACTUAL LOS = 030LOS 50P AND 75P = 04,06ACTUAL LOS = 030ISCHARGE ORDER = 0
 6294476 117210152 1012110062101760066 562P 04065641 04069
 6294476 2 11174262 000110
 629447605 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 1 0 0 0 0 0 0
 6294476 JUDGMENT = 0 ASSIGNED TO GROUP 0 LOGIT = -0.0428
 6294476 CLOS 50P AND 75P = 04,06ACTUAL LOS = 050LOS 50P AND 75P = 04,06ACTUAL LOS = 060ISCHARGE ORDER = 0
 9294476 1172101522 21015410062101760096 562P 04065641 04069
 9294476 2 11174262 000110
 929447605 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0
 9294476 JUDGMENT = 0 ASSIGNED TO GROUP 0 LOGIT = -0.3918
 9294476 CLOS 50P AND 75P = 04,06ACTUAL LOS = 090LOS 50P AND 75P = 04,06ACTUAL LOS = 090ISCHARGE ORDER = 0
 2294476 117261117 11310610073102240035 7056 02035694 542 05009
 2294476 2 1009548 0508 000159
 229447605 1 0 1 0 0 1 1 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0

[illegible]

[illegible]

3294910	JUDGMENT = 0	ASSIGNED TO GROUP 0	LOGIT = -0.9425						
3294910	CLOS 50P AND 75P = 05,06ACTUAL LOS = 070LOS 50P AND 75P =	05,06ACTUAL LOS = 070DISCHARGE ORDER = 1							
2294928	117310782	10181012110246006	4479	05,084439	83399305089				
2294928	JUDGMENT = 0	ASSIGNED TO GROUP 1	LOGIT = 0.8203						
2294928	CLOS 50P AND 75P = 05,06ACTUAL LOS = 060LOS 50P AND 75P =	05,06ACTUAL LOS = 060DISCHARGE ORDER = 0							
5294928	117310782	102131012110246006	4479	05,084439	83399305089				
5294928	JUDGMENT = 0	ASSIGNED TO GROUP 0	LOGIT = -0.391P						
5294928	CLOS 50P AND 75P = 05,06ACTUAL LOS = 090LOS 50P AND 75P =	05,06ACTUAL LOS = 090DISCHARGE ORDER = 0							
8294928	117310782	11024610121102460126	4479	35084430	83399305089				
8294928	JUDGMENT = 0	ASSIGNED TO GROUP 0	LOGIT = -0.9425						
8294928	CLOS 50P AND 75P = 05,06ACTUAL LOS = 120LOS 50P AND 75P =	05,06ACTUAL LOS = 120DISCHARGE ORDER = 1							
1295006	1140208211	21015410132110750026	7752	02043105	03059				
1295006	JUDGMENT = 1	ASSIGNED TO GROUP 1	LOGIT = 4.0986						
1295006	CLOS 50P AND 75P = 02,04ACTUAL LOS = 020LOS 50P AND 75P =	02,04ACTUAL LOS = 020DISCHARGE ORDER = 0							
4295006	1140201211	11022410132110750006	7752	02043105	03059				
4295006	JUDGMENT = 0	ASSIGNED TO GROUP 0	LOGIT = -0.9425						
4295006	CLOS 50P AND 75P = 02,04ACTUAL LOS = 090LOS 50P AND 75P =	02,04ACTUAL LOS = 090DISCHARGE ORDER = 0							
7295006	1140204211	1326110132110750136	7752	02043105	03059				
7295006	JUDGMENT = 1	ASSIGNED TO GROUP 1	LOGIT = 0.2544						
7295006	CLOS 50P AND 75P = 02,04ACTUAL LOS = 130LOS 50P AND 75P =	02,04ACTUAL LOS = 130DISCHARGE ORDER = 0							
2295010	1075117733	101651014310101025	2335	03041880	573	04069			

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1295244	1127400423	11123510170102640066	77037865	33047709	966	02059
1295244	2	10246951				
1295244	0	0 1 0 0 1 0 0 0 0 0 0 1 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0	0			000078
1295244	JUDGMENT = 0	ASSIGNED TO GROUP 0	LOGIT = -0.2425			
1295244	CLOS 50P AND 75P = 33,06ACTUAL LOS = 350LOS 50P AND 75P =					05,16ACTUAL LOS = 06DISCHARGE ORDER = 0
1295317	1185103074	1030510187113170126	8294	753	14180202	793
1295317	2	1101732				
1295317	0	0 1 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	0			000169
1295317	JUDGMENT = 0	ASSIGNED TO GROUP 0	LOGIT = -0.3414			
1295317	CLOS 50P AND 75P = 14,18ACTUAL LOS = 120LOS 50P AND 75P =					14,18ACTUAL LOS = 120DISCHARGE ORDER = 0
1295331	1142510352	2102670107110170275	7740410P	0204422		05079
1295331	2					000149
1295331	0	1 1 1 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0	0			9
1295331	JUDGMENT = 1	ASSIGNED TO GROUP 1	LOGIT = 1.1165			
1295331	CLOS 50P AND 75P = 02,06ACTUAL LOS = 070LOS 50P AND 75P =					05,07ACTUAL LOS = 070DISCHARGE ORDER = 0
4295331	1142510352	102941017110170115	7740410P	0204422		05079
4295331	2					000149
4295331	0	0 1 0 1 0 0 1 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0	0			9
4295331	JUDGMENT = 0	ASSIGNED TO GROUP 0	LOGIT = -0.3918			
4295331	CLOS 50P AND 75P = 02,06ACTUAL LOS = 110LOS 50P AND 75P =					05,07ACTUAL LOS = 110DISCHARGE ORDER = 0
1295349	11392100512	101011019111130005	411	04064101		13179
1295349	2	11014101	1317	111131051111277	1111250	000239
1295349	0	0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0	0			9
1295349	JUDGMENT = 1	ASSIGNED TO GROUP 0	LOGIT = -0.0428			
1295349	CLOS 50P AND 75P = 34,06ACTUAL LOS = 030LOS 50P AND 75P =					13,17ACTUAL LOS = 00DISCHARGE ORDER = 0
4295349	11425103512	11024510191111130045	411	04064101		13179
4295349	2	11014101	1317	111131051111277	1111250	000239
4295349	0	0 0 0 0 1 0 0 0 0 0 1 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0	0			9
4295349	JUDGMENT = 1	ASSIGNED TO GROUP 1	LOGIT = 0.5303			
4295349	CLOS 50P AND 75P = 34,06ACTUAL LOS = 360LOS 50P AND 75P =					13,17ACTUAL LOS = 06DISCHARGE ORDER = 0
7295349	1139200712	126611019111130075	411	04064101		13179
7295349	2	11014101	1317	111131051111277	1111250	000239
7295349	0	0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0	0			9
7295349	JUDGMENT = 1	ASSIGNED TO GROUP 1	LOGIT = 0.8203			

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3295459 JUDGE = 0 ASSIGNED TO GROUP 0 LOGIT = -0.9425
 3295458 CLOS 50P AND 75P = 05,07ACTUAL LOS = 05DLOS 50P AND 75P = 05,09ACTUAL LOS = 05DISCHARGE ORDER = 1
 1295490 113510221 10231022110540015 496 0507486 05389
 1295490 2 11053381
 1295490 1 1 0 0 0 1 1 0 0 0 0 1 0 0 1 0 0 0 0 0
 1295490 JUDGE = 1 ASSIGNED TO GROUP 1 LOGIT = 1.3633
 1295490 CLOS 50P AND 75P = 05,07ACTUAL LOS = 05DLOS 50P AND 75P = 05,09ACTUAL LOS = 05DISCHARGE ORDER = 0
 1295499 10325134631 103051022110170106 7991 0407251725P 06999
 1295499 2 000120
 1295499 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0
 1295499 JUDGE = 0 ASSIGNED TO GROUP 0 LOGIT = -0.9425
 1295499 CLOS 50P AND 75P = 06,07ACTUAL LOS = 06DLOS 50P AND 75P = 06,09ACTUAL LOS = 06DISCHARGE ORDER = 0
 1295512 1060633254 102310211102330076 7253 36097253 805 10149
 1295512 2 1022330 1115
 1295512 0
 1295512 JUDGE = 0 ASSIGNED TO GROUP 0 LOGIT = -0.9425
 1295512 CLOS 50P AND 75P = 11,15ACTUAL LOS = 07DLOS 50P AND 75P = 13,14ACTUAL LOS = 07DISCHARGE ORDER = 1
 1295567 1125511126 11024610224102720025 57515740 33045751 51198307089
 1295567 2 102351198307081023 470
 1295567 0 1 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 1295567 JUDGE = 1 ASSIGNED TO GROUP 1 LOGIT = 1.9868
 1295567 CLOS 50P AND 75P = 07,08ACTUAL LOS = 02DLOS 50P AND 75P = 07,06ACTUAL LOS = 02DISCHARGE ORDER = 0
 4295567 1125511126 102721022410720055 57515740 33045751 51198307089
 4295567 2 102351198307081023 470
 4295567 0 0 1 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0
 4295567 JUDGE = 0 ASSIGNED TO GROUP 0 LOGIT = -0.3414
 4295567 CLOS 50P AND 75P = 07,08ACTUAL LOS = 05DLOS 50P AND 75P = 07,08ACTUAL LOS = 05DISCHARGE ORDER = 1
 3295571 1151531215 10236110224102940045 7074 04071740 862 07099
 3295571 2 000079
 3295571 1 0 1 0 0 1 0 0 0 1 0 0 1 0 0 0 0 0 0 0
 3295571 JUDGE = 1 ASSIGNED TO GROUP 1 LOGIT = 0.2317
 3295571 CLOS 50P AND 75P = 05,07ACTUAL LOS = 04DLOS 50P AND 75P = 37,09ACTUAL LOS = 04DISCHARGE ORDER = 0
 1295578 1139513073 1123110213110760075 7491 04072751 033 11151

[illegible]

[illegible]

[illegible]

3296056 2 111477541114287 1114458011144120 000179
 329605605 0 0 1 0 0 0 1 0 0 0 0 1 0 0 1 0 1 0 0 0 0 0 0 0 0
 3296056 JUDGMENT = 0 ASSIGNED TO GROUP 0 LOGIT = -0.9428
 3296056 CLOS 50P AND 75P = 03,06ACTUAL LOS = 05DLOS 50P AND 75P = 03,06ACTUAL LOS = 00DISCHARGE ORDER = 0
 6296056 1960403542 21105410283111460085 44692370 030644697071 03069
 6296056 2 111477541114287 1114458011144120 000179
 629605605 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0
 6296056 JUDGMENT = 0 ASSIGNED TO GROUP 0 LOGIT = -0.9425
 6296056 CLOS 50P AND 75P = 03,06ACTUAL LOS = 08DLOS 50P AND 75P = 03,06ACTUAL LOS = 00DISCHARGE ORDER = 0
 9296056 1060408543 1108710283111460115 44692370 030644697071 03069
 9296056 2 111477541114287 1114458011144120 000179
 929605605 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0
 9296056 JUDGMENT = 0 ASSIGNED TO GROUP 0 LOGIT = -0.9425
 9296056 CLOS 50P AND 75P = 03,06ACTUAL LOS = 11DLOS 50P AND 75P = 03,06ACTUAL LOS = 11DISCHARGE ORDER = 0
 296056 1660403542 21111310283111460145 44692370 030644697071 03069
 296056 2 111477541114287 1114458011144120 000179
 29605605 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0
 296056 JUDGMENT = 0 ASSIGNED TO GROUP 0 LOGIT = -0.9425
 296056 CLOS 50P AND 75P = 03,06ACTUAL LOS = 14DLOS 50P AND 75P = 03,06ACTUAL LOS = 14DISCHARGE ORDER = 0
 1296174 1184133074 1107610305111350056 8050 08138050 08139
 1296174 2 000149
 129617405 0 1 0
 1296174 JUDGMENT = 0 ASSIGNED TO GROUP 0 LOGIT = -0.9425
 1296174 CLOS 50P AND 75P = 09,13ACTUAL LOS = 08DLOS 50P AND 75P = 09,13ACTUAL LOS = 08DISCHARGE ORDER = 0
 4296174 1184133074 21110210305111350116 8050 08138050 08139
 4296174 2 000149
 429617405 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 4296174 JUDGMENT = 0 ASSIGNED TO GROUP 0 LOGIT = -0.5935
 4296174 CLOS 50P AND 75P = 09,13ACTUAL LOS = 11DLOS 50P AND 75P = 09,13ACTUAL LOS = 11DISCHARGE ORDER = 0
 7296174 1184133074 21113510305111350146 8050 08138050 08139
 7296174 2 000149
 729617405 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 7296174 JUDGMENT = 0 ASSIGNED TO GROUP 0 LOGIT = -0.9425
 7296174 CLOS 50P AND 75P = 09,13ACTUAL LOS = 14DLOS 50P AND 75P = 09,13ACTUAL LOS = 14DISCHARGE ORDER = 1

1296474 JUDGMENT = 0 ASSIGNED TO GROUP 0 LOGIT = -0.0425
 1296474 CLOS 50P AND 75P = 06,06ACTUAL LOS = 020LOS 50P AND 75P = 06,06ACTUAL LOS = 020DISCHARGE ORDER = 1
 2296476 107410272 110071103211130056 496 492 07104023 07490
 2296476 2 111041291118496
 229647605 1 0 1 0 1 0 0 0 0 0 1 1 0 1 0 1 0 0 0 0 0 0 0
 2296476 JUDGMENT = 1 ASSIGNED TO GROUP 1 LOGIT = 0.5583
 2296476 CLOS 50P AND 75P = 07,10ACTUAL LOS = 050LOS 50P AND 75P = 07,10ACTUAL LOS = 050DISCHARGE ORDER = 0
 5296476 107410272 2111111103211130066 496 492 07104023 07109
 5296476 2 111841291118496
 529647605 1 0 1 0 0 1 0 0 0 0 1 0 0 1 0 1 0 0 0 0 1 0 0 0 0 0
 5296476 JUDGMENT = 1 ASSIGNED TO GROUP 1 LOGIT = 1.4262
 5296476 CLOS 50P AND 75P = 07,10ACTUAL LOS = 030LOS 50P AND 75P = 07,10ACTUAL LOS = 030DISCHARGE ORDER = 0
 1296494 1056601126 2110541103211113025 8790 54241206098651 54241206099
 1296494 2 1111966311119250
 129649405 1 1 0 1 0 0 1 0 0 0 1 0 0 0 1 0 1 0 0 0 0 0 0 0
 1296494 JUDGMENT = 1 ASSIGNED TO GROUP 1 LOGIT = 2.0865
 1296494 CLOS 50P AND 75P = 05,09ACTUAL LOS = 020LOS 50P AND 75P = 06,09ACTUAL LOS = 020DISCHARGE ORDER = 0
 1296511 1091103213 1107611032111240046 4439 040644003759 04069
 1296511 2 3300099
 129651105 1 1 0 1 0 1 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 1 0 0 0 0
 1296511 JUDGMENT = 1 ASSIGNED TO GROUP 1 LOGIT = 0.9148
 1296511 CLOS 50P AND 75P = 06,06ACTUAL LOS = 040LOS 50P AND 75P = 06,06ACTUAL LOS = 040DISCHARGE ORDER = 0
 4296511 1091103213 21110211032111240076 4439 040644003759 04069
 4296511 2 000039
 429651105 0 1 0 1 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 1 0 0 0 0
 4296511 JUDGMENT = 0 ASSIGNED TO GROUP 0 LOGIT = -0.0428
 4296511 CLOS 50P AND 75P = 06,06ACTUAL LOS = 070LOS 50P AND 75P = 04,06ACTUAL LOS = 070DISCHARGE ORDER = 0
 1296516 1154513227 11104311043110650305 5770 360857705602 06089
 1296516 2 000079
 129651605 1 1 0 1 0 0 1 0 0 1 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0
 1296516 JUDGMENT = 1 ASSIGNED TO GROUP 1 LOGIT = 2.8965
 1296516 CLOS 50P AND 75P = 05,08ACTUAL LOS = 030LOS 50P AND 75P = 06,08ACTUAL LOS = 030DISCHARGE ORDER = 0
 3296531 112455375 1109111056111130046 2231 02036192 65169105059

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